A Systems Analysis and Operations Research Approach to Optimizing Health Technology Allocation for Low-income Countries: The case of medical oxygen for childhood pneumonia in The Gambia

by

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A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy
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Abstract

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Medical oxygen is essential for treating childhood pneumonia - the leading cause of death in children under five worldwide. Unfortunately, oxygen is not widely available in many low-resource settings due to challenges such as cost, supply logistics, variability in oxygen demand, poor electricity supply, lack of trained staff, and inadequate maintenance capacity. Currently, no systematic approaches exist to help health systems plan appropriate oxygen supply systems that cost-effectively meet the needs of health facilities given these complex challenges.

This thesis presents a novel operations research (OR) approach to medical oxygen technology planning in low-resource settings. A decision-support model – OxOpt – was developed to identify the optimal combination of technologies that will meet the needs of health facilities facing resource constraints. The model applies a unique combination of simulation and optimization approaches never before combined to address a global health resource allocation problem. A discrete-event simulation model simulates health facility-level activities such as clinical demand for oxygen, power interruptions and equipment breakdowns, using primary and secondary data collected specifically for this context. A genetic algorithm-based optimization model identifies optimal technology strategies that will satisfy simulated oxygen needs. The model takes into account seasonal variability in oxygen demand, alternative energy options, and the costs of technology, energy and training. It also estimates the number of patients treated and lives saved as a result of recommended solutions.

The design of the OxOpt model is informed by several important analyses. A study of oxygen concentrator maintenance histories contributes previously lacking data on long-term functionality in a low-resource setting, providing insight into the cost of parts, expected lifespans, frequency of failures and technician training needs. Based on an analysis of alternative energy sources, a decision-tree was developed to guide decisions about appropriate energy choices given system costs and grid electricity availability.

OxOpt functionality is demonstrated for the case of The Gambia, through scenarios exploring healthcare equity in resource allocation, climate change, and changes in technology. An OR approach to oxygen
planning, which can be applied more broadly to other health technologies, can improve the efficient use of limited resources and identify cost-effective solutions that save lives.
For Tim and William
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Chapter 1

Introduction

1.1 Background and Motivation

Pneumonia is one of the leading causes of death in children under five worldwide. In 2015, an estimated 921,000 children died from pneumonia, and over half of these deaths (about 490,000) occurred in Sub-Saharan Africa [77]. Childhood pneumonia places a substantial burden on the health systems of low-resource settings; in 2010, there were an estimated 11.4 million cases resulting in hospital admission in developing countries [96].

Hypoxaemia, defined as low blood oxygen saturation (SpO$_2$ < 90%), is a risk factor for morbidity and mortality in childhood pneumonia and has been associated with a one to five-fold increased risk of death [79]. A recent systematic review found that the median prevalence of hypoxaemia among children with severe pneumonia in developing countries was 13.3% [IQR 9.3-37.5%], but prevalence varies considerably by region and altitude [124]. Oxygen therapy, the delivery of concentrated oxygen to a patient, is necessary for the treatment of hypoxaemia in order to increase and stabilize blood oxygen saturation levels and improve the probability of survival [152].

Although the evidence is limited, oxygen delivery systems have lead to measurable improvements in survival from childhood pneumonia in resource-constrained settings. For example, in Malawi, case-fatality fell from 18.6% to 8.4% after the implementation of a national program involving the installation of oxygen concentrator treatment systems [43]. In a study of 10,000 children in Papua New Guinea, a 35% reduction in case-fatality was reported after a system based on oxygen concentrators and hypoxaemia detection with pulse oximetry was installed [41]. Having a reliable supply of oxygen is thus viewed as an important part of ending preventable child deaths globally [10, 27, 38, 151].

Despite its known clinical benefit and proven effectiveness in reducing mortality from pneumonia, oxygen treatment is still not widely available in many low- and middle-income countries (LMICs). Studies have shown that only 25 to 44% of district hospitals and health centres in many developing countries have access to a continuous oxygen supply [8, 35, 53]. In The Gambia, for example, only 3 out of the 11 health centres managing severe pneumonia had a reliable oxygen supply in 2008 [61].

The two most common technology options for oxygen delivery in low-resource settings are compressed gas cylinders and oxygen concentrators. Gas cylinders require regular and costly refills and are difficult to transport to remote health facilities. Oxygen concentrators, which are portable machines that separate nitrogen from atmospheric air to produce therapeutic levels of oxygen (~ 90% pure), have been shown to
be more cost-effective than cylinders [34,63,76,91,105], but require maintenance and a reliable electricity supply, which is often absent in low-resource settings [1, 8, 61, 69]. The lack of reliable power remains one of the major barriers to the successful use of oxygen concentrators in many countries, including The Gambia, where many health facilities have electricity for just over 12 hours a day [61]. In order to reap the benefits of unlimited oxygen afforded by oxygen concentrators, energy sources such as batteries and photovoltaics are being explored as alternative options for powering concentrators where the grid supply is unreliable [17,118,133]. However, the capital investment required for such systems is substantial, and cost-effectiveness needs to be demonstrated if these solutions are to be feasibly scaled.

The lack of sufficient and reliable oxygen supplies in low-resource settings is a function of complex challenges related to cost, available technologies, supply logistics (e.g., vehicles, fuel, road systems, etc.), variability in oxygen demand across health facilities and throughout the year, erratic electricity supply, lack of trained staff, and inadequate maintenance capacity [53, 61, 152]. Analytical approaches that take these complex challenges into consideration are needed for evaluating context-appropriate and cost-effective oxygen technology solutions for health facilities with limited financial resources and unreliable power.

1.2 Problem Statement

This thesis considers the challenge of supplying oxygen in low-resource settings specifically for childhood pneumonia, and in particular aims to address the lack of analytical approaches for effective oxygen technology decision-making and planning in these settings. This oxygen supply and demand problem has been conceptualized in Fig. 1.1.

First, consider a network of health facilities that needs to supply oxygen to patients. These facilities might comprise a regional health district, or perhaps represent all the major hospitals and health centres in a country. Due to their different geographic locations and catchment areas, children are admitted to these facilities at different rates, resulting in different levels of oxygen need. Ideally, the supply of oxygen available at each facility should meet these needs in order to minimize child pneumonia deaths, but reliability of supply is affected by factors such as the oxygen sources available, maintenance needs of the equipment, on-site maintenance capacity, availability and cost of electricity, and road accessibility (Fig. 1.1).

In settings with intermittent electricity, technology solutions that compensate for unreliable power are needed. However, since each facility likely experiences different grid availability, the most appropriate alternative energy source in each setting is also likely to be very different. In addition, each facility may not have a local trained technician available on-site for concentrator repairs, necessitating additional expenses to dispatch a maintenance worker from a neighbouring facility when repairs or maintenance are required.

Finally, the cost associated with setting up and maintaining this oxygen supply system must be considered. In some cases, there may be a limited budget that needs to be appropriately allocated across these health facilities to maximize health outcomes. In other cases, decision-makers may be interested in understanding how much it will cost to meet different levels of oxygen demand. In either scenario, there will be trade-offs to consider in terms of how equitably resources are distributed, oxygen needs are met, and lives are saved, across these different facilities. Ultimately, the goal is to ensure that potentially life-saving oxygen equipment is available and included in health planning budgets [152].
Analytical approaches are needed to analyze this complex supply and demand problem, and to make recommendations for how to allocate oxygen technologies and budgetary resources in order to optimize the use of limited resources and maximize health outcomes. The following two subsections will discuss several challenges that need to be addressed, on the supply and demand side, in order to achieve this goal.

1.2.1 Demand-side challenges

On the demand side, despite available global and national estimates for the burden of childhood pneumonia, there are very little data on the volume of oxygen required to meet the needs of populations on a local level. Globally, acute respiratory infections (ARI) among children follow a seasonal trend \cite{94,95} so the demand for oxygen will vary throughout the year. Furthermore, the required flow rate of oxygen delivered to an individual patient will vary depending on the patient’s age and condition \cite{152}. For settings that rely on cylinders, records of the volume of oxygen used over the course of a day, week, month or year are scarce, not to mention estimates of how much oxygen was not provided to patients in need when supplies were depleted.

On a more macro scale, global phenomenon such as climate change are contributing to changes in disease patterns. The World Health Organization (WHO) predicts that environmental changes brought on by unmitigated climate change will lead to significant increases in illness and death, globally \cite{89,153}. For example, there is growing evidence in Africa of an association between increased incidence and risk of death from acute respiratory infection with increasing temperature \cite{5,90,129,131}. As a result, the demand for oxygen is likely to increase in the future but it is unknown how robust existing technology
solutions may be to these changing needs, or how much additional resources may be needed to cope with the effects of changing disease patterns.

1.2.2 Supply-side challenges

On the supply side, oxygen concentrators have already been established as a suitable option for administering point-of-care oxygen in developing countries, especially where cylinders are inappropriate or unavailable [152]. Yet methods for properly sizing the fleet of concentrators required to service the needs of a district, region, or country are not available, especially given the demand-side challenges discussed above. Some programs have determined equipment quantities based on average monthly oxygen demand estimates, but this approach likely underestimates seasonal peaks in demand [86]. An analysis of concentrator costs for health facilities in The Gambia used the WHO recommendation of one concentrator to every 10 to 15 beds, with one additional backup concentrator. This analysis assumed reliable electricity from the grid or a generator and did not consider alternative energy sources [63]. Regardless of the approach used to plan for the use of concentrators, another challenge is that evidence of the functioning of concentrators beyond three years in a low-resource setting is scarce [73, 91], and thus little is known about the long-term reliability of these devices.

Furthermore, new oxygen technologies are being piloted, for example solar-powered concentrators [133] and electricity-free oxygen generating machines [122], but it is unknown how well these systems will compare against what is currently available. Methods are needed to compare the cost of such new innovations to existing technologies in order to determine how appropriate such novel systems would be in different contexts. Such analyses could also help indicate target price points for new innovations such that they are competitively cost-effective with current existing solutions.

1.2.3 Operations research: The solution approach

Operations research (OR), a discipline that uses advanced analytical methods (e.g., simulation, optimization, decision analysis) to better understand complex systems and aid in decision-making, is well suited to fill this gap. OR methods can be used to systematically analyze different oxygen technology options given all of the contextual factors mentioned above, and ultimately identify the most appropriate and cost-effective solutions.

1.3 Thesis Objectives

This thesis aims to address the challenge of supplying oxygen in low-resource settings through three main objectives, as follows:

- **Objective 1**: Demonstrate that systems thinking and operations research can be applied to complex global health challenges to aid in policy- and decision-making, specifically for health technologies.

- **Objective 2**: Develop an evidence-based OR decision model for the allocation of medical oxygen technologies across a health system, which takes into account oxygen demand dynamics, electricity availability, alternative energy options, and maintenance needs.
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- **Objective 3:**
  
  (a) Apply the model to the case of The Gambia, an example low-resource setting, to make recommendations for improving the oxygen supply across the entire health system and estimate the cost-effectiveness and lives saved as a result of implementing the model’s recommendations.

  (b) Apply the model to additional hypothetical scenarios to demonstrate the model’s functionality and utility as an advocacy tool, showing that an increased investment in oxygen supplies can cost-effectively save lives. Specifically, apply the model to test health equity-related scenarios, scenarios with increased disease burden due to climate change, and innovation-related scenarios.

  To achieve Objective 1, this thesis presents the first-ever scoping review of operations research in global health to better understand how these analytical techniques have been used for global health challenges. A significant contribution in its own right, this review highlighted some important gaps in the literature that this thesis aims to fill - specifically, the application of OR in a low-income country to address issues in medical technology planning. This review also helped inform several aspects of this research, namely, the importance of: local collaborators, local input data, the communication of research findings and the consideration health equity in OR analyses - all of which have been incorporated into this research.

  A major prerequisite for Objective 2 was building a strong evidence base for the choice and suitability of the technology solutions to be proposed by the model, namely oxygen concentrators and alternative energy sources for these devices. This involved a retrospective analysis of the maintenance needs of oxygen concentrators in a low-resource setting, to understand why and how often these devices fail. A follow-up study on the implications of these maintenance needs for technician training was also conducted, providing insight into a skills-based approach to oxygen concentrator maintenance training in resource-limited settings.

  Building this evidence base also involved an in-depth exploration of alternative energy options for concentrators (i.e., UPS, battery backup, solar power), their system configurations and components, attributes and limitations, and field experience in low-resource settings, which ultimately led to the development of a decision-tree to guide decisions about which options are likely most appropriate in which settings.

  Oxygen concentrators are the only oxygen source considered in this research, for several reasons. Firstly, the WHO endorses this technology for oxygen supply on its ‘List of Priority Medical Devices’ for newborn and child health [156], and has further supported their use with the recent release of a Technical Specifications for Oxygen Concentrators document [152], which defines requirements for oxygen concentrators that are appropriate for the treatment of hypoxaemia in developing countries. This document is intended to be used in conjunction with the current standard for oxygen concentrators (ISO 80601-2-69:2014). Furthermore, at present, there are no revolutionary oxygen technologies for medical use under consideration for ISO standardization; thus the oxygen systems considered in the model are currently the best available for this context. The aim and scope of this work is not to recommend new technologies but to evaluate in a more effective way existing technologies in new configurations that are appropriate for low-resource settings.

  The decision-support model of Objective 2 – named the OxOpt model – was implemented using a simulation-optimization structure to (a) simulate health facility-level oxygen supply and demand dynamics, and (b) determine optimal technology strategies that will cost-effectively meet the oxygen needs
Chapter 1. Introduction

The model takes into account seasonal variability in oxygen demand, electricity availability, alternative energy options, technology and energy costs, equipment breakdowns and maintenance, and patient outcomes. The simulation component uses discrete-event simulation techniques, and the optimization component is solved via a genetic algorithm.

The model has two main functions; to act as a decision-support tool or a theoretical analysis tool. When used as a decision-support tool, the model determines which oxygen technologies will meet the needs of a specific context and at what cost. As a theoretical tool, the model can be used to advocate for investments in oxygen by demonstrating the cost-effectiveness of oxygen therapy for a wide range of different scenarios and contexts and showing the tradeoff between cost and unsatisfied demand. It can also be used to analyze ‘what if’ scenarios that explore how changes to the factors affecting oxygen supply and demand will affect model recommendations.

The model is targeted towards ministries of health and hospital administrators in public health systems with decision-making authority, or philanthropic or not-for-profit organizations who want to fund programs to improve oxygen availability and want to properly plan the technology allocation according to the needs of different populations. In either case, it is assumed that the model would be used within the context of a broader health needs assessment (HNA) - the systematic and evidence-based process of identifying unmet health and healthcare needs of a population, and the commissioning and planning of health services to meet these unmet needs [157,158]. This HNA process involves an in-depth situational analysis followed by an analysis of available options, which is where the OxOpt model would be most beneficial.

For Objective 3, OxOpt model functionality is demonstrated for the case of childhood pneumonia in The Gambia. This case study is presented in the context of a HNA; first, a situational analysis provides the necessary background and input for the model, then, different scenarios are presented with model results and recommendations.

In summary, this thesis aims to marry the theoretical with the practical, using sound methodologies from operations research that are grounded in real-world evidence, data and experiences. The design of the OxOpt model has been informed by months spent in the context of The Gambia working with local biomedical engineering technicians, medical gas experts, and research clinicians specializing in child health and childhood pneumonia, specifically. The solution approach – operations research – is increasingly being used to analyze complex global health challenges, but is under-utilized as an approach to medical technology planning in low-resource settings. OR can be used to demonstrate that oxygen is a cost-effective intervention that can save lives, both now and in the future, given growing demands on health systems due to our changing climate, as well as advances in technology and innovation that could help alleviate these extra demands on resources.

1.4 Organization of Thesis Document

The chapters in this thesis are a combination of both published and unpublished work, as shown in Fig. 1.2. This chapter presents the background and motivation behind the thesis and the specifics of the problem being addressed. Chapter 2 is an executive summary of a scoping review on the use of OR in global health (the full publication is provided in Appendix A).

Chapters 3, 4 and 5 present work related to challenges with oxygen supply and demand in low-resource settings. Chapter 3 includes the retrospective study of oxygen concentrator maintenance needs in The
Chapter 1. Introduction

Gambia as well as the follow-up study on the implications of these maintenance needs for technician training. Chapter 4 provides a summary of the alternative energy options considered in the model. Chapter 5 presents a publication on a discrete-event simulation (DES) model that was developed to estimate demand for oxygen in low-resource health facilities based on five key factors: annual pneumonia admission rate, hypoxaemia prevalence, degree of seasonality, treatment duration, and oxygen flow rate.

Figure 1.2: Organization of Thesis. Chapters that are published works are indicated. OR: Operations research.

Chapters 6, 7 and 8 all pertain to the OxOpt model. Chapter 6 provides an introduction to the health needs assessment process, and describes how the OxOpt model is intended to be used within this framework. In Chapter 7, a detailed description of the design and mathematical formulation of the OxOpt model is presented, including the DES model of Chapter 5 and the genetic algorithm optimization approach. Finally, the OxOpt model is applied to the case example of The Gambia in Chapter 8, which includes an in-depth situational and options analysis, application of the model, and scenarios related to healthcare equity, climate change, and technology and innovation.

Lastly, conclusions and future work are presented in Chapter 9.
1.5 Thesis Contributions

Drawing upon operations research methodologies and global health practice, this thesis presents an interdisciplinary approach to a major global health challenge. The OxOpt model uniquely combines two OR methodologies – discrete-event simulation and genetic algorithm optimization – to quantify and propose technological solutions to the medical oxygen supply and demand problem in low-resource settings, a global challenge that has never before been analyzed with a systematic operations research approach.

Specifically, the culmination of this work has led to the following major contributions:

- The most recent and comprehensive literature review of the use of operations research in global health since 1993, which highlights the geographical reach of OR studies and the use of different OR methods across different application areas of global health.

- The first-ever longitudinal analysis of oxygen concentrator reliability and maintenance needs in a low-resource setting, which underscored the importance of a support framework for trained technicians and routine preventive maintenance and led to the identification of a minimum set of technician skills needed to repair the majority of concentrator failures. This study will be beneficial for project planners interested in implementing oxygen concentrators in health facilities in LMICs.

- The largest body of literature describing and comparing alternative energy systems for oxygen concentrators as presented at international conferences and in proceedings.

- A novel DES model for estimating oxygen demand in low-resource health facilities in the absence of longitudinal clinical data for the purposes of oxygen technology planning. There have been no modeling approaches to the problem of estimating demand for oxygen in low-resource settings.

- A novel evidence-based decision-support and advocacy tool – the OxOpt model – which combines the DES model above with other health facility-level simulation modules and an optimization model to recommend optimal oxygen technology systems, including alternative energy technologies, to improve oxygen availability and save lives in low-resource settings. To date, there have been no analytical tools available to simultaneously quantify oxygen supply and demand in order to optimize oxygen technology planning.

Elements of this research are already having a meaningful impact. For example, research addressing supply-side challenges from Chapter 3 [18] and Chapter 4 [17, 22] has been cited in the WHO’s Technical Specifications for Oxygen Concentrators [152]. The work of Chapter 3 was also cited in a recent Textbook of Global Health [12] as an example of a collaborative effort towards providing equipment and technology in a low-resource setting that considers training and maintenance - important building blocks of health care systems.
Chapter 2

Literature Review: Operations Research in Global Health

This chapter provides a summary of a published review article (full citation: Bradley, BD et al. Operations Research in Global Health: A scoping review with a focus on the themes of health equity and impact. Health Research Policy and Systems, 15:32, 2017 [20]). The published version of the article is provided in Appendix A under the Creative Commons Attribution (CCBY) License.

2.1 Abstract

Operations research (OR) is a discipline that uses advanced analytical methods (e.g., simulation, optimization, decision analysis) to better understand complex systems and aid in decision-making. This paper presents a scoping review of the use of OR to analyze issues in global health, with an emphasis on health equity and research impact. A systematic search of five databases was designed to identify relevant published literature. A global overview of 1099 studies highlights the geographic distribution of OR and common OR methods used. From this collection of literature, a narrative description of the use of OR across four main application areas of global health – health systems and operations, clinical medicine, public health, and health innovation – is also presented. The theme of health equity is then explored in detail through a subset of 44 studies. Health equity is a critical element of global health that cuts across all four application areas, and is an issue particularly amenable to analysis through OR. Last, we present seven select cases of OR analyses that have been implemented or have influenced decision-making in global health policy or practice. Based on these cases, we identify three key drivers for success in bridging the gap between OR and global health policy: international collaboration with stakeholders, use of contextually appropriate data, and varied communication outlets for research findings. Such cases, however, represent a very small proportion of the literature found. Poor availability of representative and quality data, and a lack of collaboration between those who develop OR models and stakeholders in the contexts where OR analyses are intended to serve, were found to be common challenges for effective OR modeling in global health.
2.2 Implications of the Review for this Thesis

This review has important implications for this thesis in two key areas: (1) identifying gaps where OR has least been applied in global health, further underscoring the contributions made by this research; and (2) highlighting important considerations when conducting OR in a low-resource setting.

2.2.1 Contribution to OR for global health

Three major gaps were identified that this thesis aims to address. First, OR has been disproportionately applied in middle-income countries. OR studies in low-income countries, which arguably have more to gain from systematic analyses of global health challenges due to strict resource constraints, represent only 17% of the literature reviewed. The focus of this thesis is on The Gambia, a low-income country in West Africa. Not only does this research add to the dearth of OR studies applied to low-income countries, it provides important primary and secondary data collected in this setting (i.e., concentrator maintenance logs and health facility-level power interruption data) which are useful contributions towards a better understanding of the challenges of oxygen supply and demand in low-resource settings.

Second, very few papers (about 1%) were found to address issues related to medical equipment and health technology management. Examples include studies about increasing vaccine cold storage equipment [58, 59], a cost-utility analysis of introducing PET scanning technology for lung cancer diagnosis in Iran [117]; a simulation model of a mammography clinic in Brazil that took into account equipment failures and maintenance [29]; a queuing model developed to improve response and turn-around time of equipment repair work orders in a clinical engineering department in Cuba [30]; and models to help inform general medical equipment purchasing [107] and replacement schedules [100] in LMICs. The OxOpt model uniquely combines elements of equipment breakdowns and maintenance with patient demands on these equipment resources in order to quantify and minimize the mismatch between supply and demand.

Third, no global health OR studies were found to combine discrete-event simulation and genetic algorithm optimization. Some of the medical equipment-related studies above used discrete-event simulation, but not in combination with optimization. In fact, just five out of 1099 studies reviewed (0.5%) used a combination simulation-optimization approach: two of which used DES and optimization, but neither used genetic algorithm as the optimization solver. These studies included a model to help reduce waiting times in a health center in Colombia [104] and a model to optimize ambulance positioning and response time for an urban city in Brazil [120]. None of the sim-opt models were related to resource allocation for medical equipment planning.

2.2.2 Considerations for conducting OR in low-resource settings

Other insights gained from the scoping review were related to key drivers for success in bridging the gap between OR and global health policy, namely: international collaboration with stakeholders, use of contextually appropriate data, and varied communication outlets for research findings. To the extent possible, these strategies have been implemented throughout this research.

From the outset, this research has been carried out in collaboration with the Medical Research Council (MRC) Unit, The Gambia. Through this collaboration, stakeholders involved in all aspects of the oxygen supply and demand problem in The Gambia and similar low-resource settings have provided invaluable insights that have informed the design and development of the OxOpt model. Stakeholders included: child health research clinicians specializing in childhood pneumonia, nurses and physicians...
working in paediatric wards where oxygen supplies are scarce, international medical gas consultants familiar with oxygen technologies, and local Gambian biomedical engineering technologists familiar with the technological barriers to reliable oxygen supply.

A concerted effort has also been made to ensure the model is as evidence-based as possible. All model parameters and inputs are based on data collected in the field as part of this research or from published literature. Furthermore, all of the oxygen technology options considered in the model have been proven in the field, either in The Gambia or elsewhere.

Last, a variety of communication outlets have been pursued for various research outputs. For example, elements of this research have been presented at local and international conferences focused on technology in low-resource settings, such as the IEEE Global Humanitarian Technology Conference, the IET Appropriate Healthcare Technology Conference, the WHO Global Forum on Medical Devices, and the World Congress of Biomedical Engineering. Additionally, major portions of this research have been published in peer-reviewed journals [18–21]. Although implementation of model recommendations is considered outside the scope of this thesis, there will be a continued effort beyond the completion of this dissertation to disseminate model recommendations for The Gambia to stakeholders at the MRC and their Ministry of Health partners.
Chapter 3


This chapter contains two previously published papers; section 3.1 is a journal paper on the maintenance needs of oxygen concentrators in a low-resource setting, and section 3.2 is a conference paper on a skills-based training approach for the maintenance of oxygen concentrators. Section 3.3 presents a summary of OxOpt model design considerations and features based on these two analyses.

3.1 A Retrospective Analysis of Oxygen Concentrator Maintenance Needs and Costs in a Low-resource Setting: Experience from The Gambia

This work has been previously published (full citation: Bradley, B. D. et al. A retrospective analysis of oxygen concentrator maintenance needs and costs in a low-resource setting: experience from The Gambia. Health and Technology, 4(4):319-328, 2015 [18]). It has been reproduced here (sections 3.1.1 - 3.1.6) without changes. Permission to use this content was secured through RightsLink.

3.1.1 Abstract

Oxygen is an essential medicine for the treatment of pneumonia, the leading cause of death in children under five worldwide. Yet, providing a sufficient and reliable supply of oxygen is a major challenge for many health facilities in the developing world, particularly in paediatric care units. The cost-effectiveness of oxygen concentrators versus compressed gas cylinders as a source of oxygen in low-resource health facilities has been demonstrated, but evidence of their long-term functionality is scarce. The Biomedical Engineering Department at the Medical Research Council Unit in The Gambia manages and maintains 27 oxygen concentrators at several sites across the country, and has kept electronic records of all preventive maintenance checks and repairs on these devices since 2006. Through a retrospective analysis of these maintenance records, the objective of this study was to assess the long-term reliability and maintenance
needs of oxygen concentrators in a low-income setting with biomedical engineering technologist support. We found that the majority of concentrator repairs are low-cost and require a low experience level to complete. We estimate that the useful lifespan of oxygen concentrators in low-resource settings could reasonably exceed 7 years provided a system is in place for routine preventive maintenance. We conclude the paper with additional insights on the broader support ecosystem required to manage and maintain oxygen concentrators in low-resource settings.

3.1.2 Introduction

Although global child mortality rates have fallen dramatically over the past couple of decades, pneumonia remains a leading cause of death in children under five, accounting for an estimated 1.3 million deaths in 2011 [47]. Providing appropriate oxygen therapy can help reduce pneumonia-related mortality by as much as 35% [41]. Yet, providing a sufficient and reliable supply of oxygen in paediatric care units is a major challenge for many health facilities in the developing world [61, 137]. Where oxygen is available, demand often outstrips available supply [45], and competition for oxygen by other services can leave many admitted hypoxaemic children without access to this life saving resource [53].

A common source of oxygen in developing countries is compressed gas cylinders, but they are costly to refill and the logistics of transporting them are challenging, especially for remote health facilities [42, 91, 137]. Oxygen concentrators, stand-alone medical devices that generate concentrated oxygen from ambient air, have been proposed as a more cost-effective alternative to cylinders [40, 41]. With appropriate mechanisms to divide the flow, oxygen concentrators can supply oxygen to multiple patients simultaneously [40]. The expected lifespan of concentrators relates to the guaranteed life, which according to manufacturers’ warranties, ranges from 1 to 5 years [102,103].

Dating back to the early 1990’s, several small-scale studies in low-resource settings have demonstrated that oxygen concentrators are more cost-effective than cylinders, reporting cost savings of up to 75% [34,76,91,105]. A theoretical analysis from The Gambia showed that where power is reliable, concentrators are more cost-effective than cylinders even if replaced every 5 years [63]. Larger programmes coordinated by ministries of health, the World Health Organization (WHO) and international funders, have demonstrated that widespread use of oxygen concentrators across district hospitals in resource-constrained settings is feasible. Early field trials were conducted in Mongolia and Egypt [33], and more recent programmes have been implemented in Malawi [42, 43] and Papua New Guinea [41, 86]. These studies demonstrated promising early results and reported on the status of oxygen concentrators up to 28 months post-installation.

Evidence of the functioning of concentrators beyond 3 years in a low-resource setting is scarce [73,91], and thus little is known about the long-term reliability of these devices. There is also a lack of evidence that a strong medical technology support ecosystem can positively impact the performance and longevity of concentrators in such settings. In 2007, La Vincente et al. [73] conducted the most comprehensive assessment to date of oxygen concentrator functionality beyond 3 years of use by evaluating 62 concentrators in 24 hospital paediatric wards across Mongolia and Malawi. This analysis, however, was only able to capture a cross-sectional snapshot of functionality at the time of assessment in each facility. Furthermore, due to lack of maintenance records, they were unable to assess the role of maintenance in concentrator longevity [73].

To our knowledge, there has been no longitudinal study of the reliability of oxygen concentrators in a low-resource setting through an analysis of individual device maintenance histories. The objective of
this study is to assess the long-term performance and maintenance needs of oxygen concentrators based on our experience at the Medical Research Council (MRC) Unit, The Gambia – a low-income setting with biomedical engineering technologist (BMET) support. We present a retrospective analysis of over 5 years of oxygen concentrator maintenance records to determine common failure modes, replacement parts needed, equipment downtime, expected useful lifespan, and annual repair costs. Furthermore, we use this analysis to provide insight into the support ecosystem required to manage oxygen technology in a low-resource setting, including the level of BMET experience and training required to effectively maintain concentrators in low-resource health systems.

3.1.3 Study setting and methodology

Study setting

*Medical equipment management at the Medical Research Council Unit in The Gambia*

The MRC in The Gambia, established in 1947 as the UK’s single largest investment in health research in a developing country, presents an interesting case through which to explore the issue of oxygen concentrator longevity in a low-resource setting. Between 2004 and 2006, a fully functional biomedical technology management program was established at the Unit’s main site in Fajara [128]. In 2006, this newly formed Biomedical Engineering (BME) department introduced an electronic equipment management database (AIMS; Phoenix Data Systems Inc., Southfield, MI) for the scheduling and reporting of preventive and corrective maintenance on all supported equipment. By 2011, the department had implemented a quality system [56] based on principles outlined in Managing Medical Devices: Guidance for healthcare and social services organizations [135] and Good Clinical Laboratory Practice [146]. Today the BME department consists of a department head (a biomedical engineer), one senior BMET, four BMETs, two assistant BMETs, and a rotation of two interns from the local electronics trade college. A high school diploma and college-level electronics diploma are minimum requirements to work in the BME department. The team manages and services 99% of the Unit’s biomedical technologies at their in-house workshop – some 1800 pieces of clinical and laboratory equipment with wide-ranging complexity and service needs [97,98].

Twenty-seven bedside oxygen concentrators, acquired between September 2006 and November 2011, are located at the MRC’s on-site 42-bed secondary-care hospital as well as at other field stations and health facilities throughout the country where the MRC conducts collaborative research. All concentrators are from the same manufacturer, Airsep Corp (Buffalo, NY), and are one of three models, Newlife Intensity, Newlife Elite or Visionaire. Electronic records of preventive maintenance, repairs, and inventory inspections for these devices have been kept since September 2006.

*Preventive maintenance protocol for oxygen concentrators*

The major components of an oxygen concentrator include: air intake and internal filters, a compressor, valves, sieve beds and a printed circuit board (PCB) [40]. Procedures for regular user and preventive maintenance are neither laborious nor complex. Recommended user maintenance by clinical staff includes weekly washing of the air intake filter and periodic cleaning of the exterior with a mild disinfecting cleaning agent [40]. Preventive maintenance performed by technicians is recommended at
least every 6 months, and includes testing the oxygen concentration at both low and maximum flows with a calibrated oxygen analyzer, removing the outer casing and thoroughly cleaning the interior of the machine, checking batteries, and inspecting internal filters [40].

At the MRC, oxygen concentrators are subject to inventory and inspection checks at least once per year. These checks ensure that concentrators are in their designated locations, and missing devices can be identified. Beginning in 2008, major preventive maintenance checks have been scheduled annually, and minor preventive maintenance checks every 3 months, subject to technician availability, especially for concentrators located at remote sites, which requires travel. A technician from the main site visits each MRC field site every 3 months to perform inspections, scheduled preventive maintenance, and repairs. If a device is not serviceable on-site, it is brought to the biomedical engineering workshop in Fajara to be serviced [128]. Preventive maintenance on oxygen concentrators is typically delegated to assistant BMETs who have had concentrator-specific training. Some preventive maintenance checks lead to the discovery of faults and result in a necessary corrective action or repair, referred to hereafter as “corrective maintenance”. Repairs are delegated to an available technologist with the necessary skills and experience.

Study methodology

Electronic work orders (WO) pertaining to oxygen concentrators between September 1, 2006 and August 14, 2013 were downloaded from the MRC’s equipment management database. Twenty-nine concentrators with 853 WOs were identified. Only stand-alone bedside models used in a clinical ward setting were of interest for this study; consequently two DC-powered portable ambulance concentrators and 45 associated WOs were excluded. Twenty-seven concentrators and 808 associated WOs were included in the final analysis (Fig. 3.1). WOs were categorized as follows: 142 inventory and inspections (IN), 633 preventive maintenance checks (PM), and 33 repairs (RE). Twenty-three of the 633 PMs (3.6%) resulted in a repair and were further classified as corrective maintenance (CM). Where possible, cumulative hours-of-use was recorded for each device at the time of analysis.

All 56 repair WOs (33 repairs and 23 PMs leading to CM), were categorized into one of 13 generic causes of failure, including an ‘unknown’ category. These failure categories describe both sub-optimal functionality (e.g., faulty oxygen outlet, filter needing replacement) and complete concentrator breakdowns (e.g., compressor failure). Repairs where simultaneous faults were identified in more than one component were categorized as a ‘multi-component failure’. Causes of failure were ranked according to increasing repair difficulty and thus increasing experience level required to complete the repair. A technician with a ‘low’ experience level would have in-house cross-training by highly skilled BME staff and/or 3 days of concentrator-specific training and less than 1 year of working experience (e.g., intern, assistant BMET), and a technician with a ‘high’ experience level would have 3 days of concentrator-specific training and more than 1 year of working experience on major PMs and repairs (e.g., BMET, senior BMET).

Spare parts required for repairs were tallied. Where a spare part was not indicated with specificity (e.g., “filter replaced”), the context of the repair was examined in more detail (e.g., who completed it, what additional repair comments were recorded, etc.) to make an informed assessment as to which type of part (e.g., internal or air intake filter) was replaced. MRC purchasing records were used to calculate the average costs of each spare part over the study period; where purchasing data were not available, the price list provided by the manufacturer was used.
Metrics computed include: mean number of INs and PMs completed per machine per year; mean time to first failure and mean time between failures; mean time to end of life (i.e., device retirement); proportion of concentrators needing repairs each year; median repair time and total equipment downtime; and cost per machine per year in service for parts replacements.

Figure 3.1: Breakdown of work orders included in study. Repair (RE) and corrective maintenance (CM) work orders were combined and further analyzed for causes of failure.

### 3.1.4 Results

Median age of the 27 concentrators (22 Newlife Intensity, 4 Newlife Elite, and 1 Visionaire) was 6.1 years [inter-quartile range (IQR): 3.3, 6.9]. Median cumulative hours of use at the time of analysis was 6,267 h [IQR: 3,566, 10,702], with an approximate annual usage of 1,480 h per machine (data available for 23 concentrators only). The longest cumulative usage was 14,591 h.

Concentrators received 3.4 ± 0.6 (mean ± standard deviation) PM checks per year in service. Figure 3.2 shows a timeline of repair and corrective maintenance events for each concentrator. Three (8%) concentrators did not require any repairs (mean age: 3.6 ± 2.9 years), and five (18.5%) required only

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1Age is calculated up until the day a concentrator was retired, was identified as missing, or Aug 14, 2013 – whichever is earliest.
CM (mean age: 5.9 ± 1.0 years). For the 19 concentrators that required non-scheduled repairs (i.e., not PM-related), median time to the first failure was 1.6 years [IQR: 1.0, 2.9]. Ten of these concentrators experienced more than one non-PM-related repair; median time between failures was 1.4 years [IQR: 1.1, 2.6]. Of the 56 failures, 53 (94.6%) were successfully resolved, two (3.6%) were still under repair at the time of analysis (both REs), and one was beyond repair due to contaminated sieve beds (also RE). This device was subsequently retired. In any given year, on average about 31% of concentrators in circulation required repairs.

In terms of equipment downtime, 37\(^2\) (69.8%) of the 53 repairs that were successfully resolved were completed on the same day the work order was raised (i.e., less than 1 day of downtime) (Fig. 3.2). Median time to complete the other 16 repairs was 80.0 days [IQR: 15.0, 146.5]. Failures taking greater than 100 days to repair included: a compressor failure (concentrator 2), faulty sieve beds (concentrators 10 and 17), and faulty PCBs (concentrators 10, 17, and 25). Causes of failure for concentrators 20 and 22 were unknown. Equipment downtime as a percentage of collective days in service was only 5.2% (Fig. 3.2).

Compressor failures occurred in three of the oldest units (concentrators 1, 2 and 3 in Fig. 3.2), after 3.6, 5.4, and 2.6 years of service, respectively. All of these concentrators were repaired and put back into service. Although hours of use data were not recorded at the time of these failures, we do know that all of these machines have, at present, operated for less than 20,000 h.

During the analysis period, 142 inventory and inspections were performed (mean of 1.4 ± 1.2 inspections per concentrator per year, not shown in figure). Based on these inventory assessments, two machines were deemed missing. In addition to these losses, two concentrators have been retired from

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\(^2\)This includes all 23 CMs, which were assumed to be same-day repairs (i.e., resolved on the day the PM was completed).
service (mean age: 6.8 ± 0.1 years) since 2006. Of the MRC’s 27 concentrators introduced since 2006, 23 (85%) are still in service and of these 21 (91%) were functional as of the date of this analysis (Fig. 3.2).

Figure 3.3 shows the frequency of repairs and corrective maintenance according to generic causes of failure, which are listed in increasing order of repair complexity. Five repairs were unclassifiable (i.e., ‘unknown’) due to lack of information recorded in the work order summary. Almost 70% of the most common repairs (filter and check valve replacements) were discovered during routine PM checks. More complex faults (e.g., sieve bed, PCB and compressor failures) typically required removing the machine from service and opening a repair work order.

The majority of concentrator faults were repairable for less than US $10 on average, and required a low experience level to repair (Fig. 3.4). The average costs of the most common repairs – filter and check valve replacements – were US $4.53 and US $6.80, respectively. The most expensive repairs – sieve bed and compressor replacements – cost approximately US $190 and US $180, respectively. Although these repairs require a higher experience level, they were rare. Multi-component failures were common and were more costly to repair on average due to multiple parts being replaced (mean cost approximately US $135). On an individual concentrator basis, median cost of repairs over the entire analysis period was US $9.44 per concentrator [IQR: US $0, US $63.40], with a maximum of US $573 for a 7-year old concentrator that has operated for 6,936 h.

Note that the average valve cost was US $5.44 but for some repairs, two or more valves were replaced, increasing the average cost per repair.
Figure 3.4: Average cost and frequency of generic causes of concentrator failure according to increasing repair difficulty (and increasing BMET experience level required to complete the repair). Circle area correlates to frequency of repair (also indicated beside label). Cost represents the cost of parts (if any) averaged across all repairs of a certain type, and does not include time for labour, hence why some repairs are US $0.

Figure 3.5 depicts the quantity of each type of spare part replaced, and the relative contribution of each part type to total spending on replacement parts. Seventy-one per cent of parts replaced contributed only 7% (approximately US $136) of the total cost; meaning the majority of repairs could be completed on a very low budget. We estimate that less than US $2,100 has been spent on replacement parts for oxygen concentrators at the MRC since 2006. This is less than 10% of the total capital cost of these devices (with purchase prices ranging from about US $500 to $1,100 [102]) and translates to approximately US $15 per machine-year of service. Five years after the first batch of concentrators was purchased (by which time all but three concentrators had been acquired), approximately US $1,210 had been spent on replacement parts.

An accurate assessment of labour costs was not possible because time spent on PMs and repairs was not routinely recorded by the BME staff. Assuming technician time to be 15 min per minor PM and 1 h per major PM, we estimate that approximately 271 h were spent conducting the 633 recorded preventive maintenance checks. An estimated 66 h were spent on non-PM-related repairs, assuming 2 h per repair. Total estimated man-hours for the up-keep of concentrators at the MRC over the 7-year analysis period is approximately 337 h.

Seventeen of the concentrators were located at the MRC’s main hospital in Fajara, and ten were distributed across three other health facilities. Three of the off-site concentrators were almost 7 years old, but the rest were introduced more recently (i.e., April 2010 or later). Median age of off-site concentrators was 2.8 years [IQR: 2.0, 6.0] compared to 6.1 years [IQR: 6.1, 7.0] for on-site concentrators. Off-site concentrators were used less, with a mean annual usage of approximately 1,229 h per machine compared to 1,629 h for those located in Fajara, but this difference was not significant ($p = 0.3$). Mean number of PM checks per machine per year was slightly less for off-site concentrators ($3.3 \pm 0.7$) compared
Figure 3.5: **Frequency and relative cost of replacement parts.** (a) Number of parts replaced since Sept 2006 according to part type and (b) Contribution (%) of different part types to total spending on replacement parts, estimated to be approximately US $2,100 in total since Sept 2006.

to on-site ones (3.4 $\pm$ 0.6), but this difference was also not significant ($p = 0.7$). Thirteen of the 56 repairs were for off-site concentrators. There was no significant difference in the frequency of repairs per machine per year in service between the two groups ($p = 0.2$). Equipment downtime as a percentage of total days in service was higher for off-site concentrators, which were out of service 9.3% of the time versus 3.6% for on-site concentrators. Ninety percent of off-site concentrators are still in use, compared to 82% of on-site concentrators; this is largely due to off-site concentrators being much newer. Total cost of spare parts for on- and off-site concentrators is estimated to be US $1,700 and US $315, respectively.

### 3.1.5 Discussion

**Repairs and failures: rare and low cost**

This analysis provides evidence that the useful lifespan of oxygen concentrators (of the type used at the MRC Unit in The Gambia, Airsep models) could reasonably exceed 7 years in a low-resource setting with BMET support. Median age of the MRC’s 27 concentrators was over 6 years, which exceeds the manufacturer’s warranty period. We found several concentrators to be operational for up to 2 years without needing a repair, and others that have operated for over 5 years without a major failure. Although we observed relatively low accumulation of hours, our findings were consistent with reported usage in similar contexts [73]. The majority of repairs (filter, battery, and valve replacements) are low-cost, and require a low experience level to complete. With 85% of all concentrators ever purchased still in circulation, and a rate of functionality of 91% as of August 2013, the MRC has experienced better long-term outcomes than were found in Malawi or Mongolia, where fleets of concentrators that were younger on average were found to be only 78% and 52% functional, respectively [73]. Concentrators located at off-site facilities do not have a worse failure record, and have received just as many PM checks per year as those at the main site. However equipment downtime is worse for off-site concentrators as many repairs require that the device be transported to the main site.
This analysis has also produced realistic estimates of the number and cost of replacement parts for the long-term maintenance of a fleet of oxygen concentrators in a low-resource setting. Such an assessment has not yet been possible due to lack of good record keeping in these settings. Filters, valves and batteries were found to be the most common parts replaced. Excluding labour costs, we estimate that concentrators can be maintained for as little as US $15 per machine-year of service, with 71% of repairs over the 7-year study period being serviceable for less than a total of US $150.

We estimate that technician labour time for preventive and corrective maintenance is relatively low. The majority of faults analyzed could be rectified by college-trained assistant BMETs. In a parallel study, we identified the specific skills required to repair observed failures, such that training for interns and assistant BMETs could be targeted towards the most common concentrator failures [16].

Efforts to increase the longevity of oxygen concentrators serve to make them even more economical than cylinders. An alternative model of sustainability that plans for concentrator replacement after 5 years would still be less costly than cylinders [63]. Thus, the achievement of lifespans exceeding 5 years at low cost by the MRC BME department adds to the evidence-base for the long-term cost-effectiveness of oxygen concentrators in low-resource settings.

The equipment support ecosystem: what does it take to achieve long-term reliability?

The “support ecosystem” required to introduce and sustainably support oxygen concentrators in low-resource health systems has been well documented by others based on lessons learned from past experiences [33, 35, 41, 42, 86, 105]. There is general agreement that a comprehensive approach to equipment management, including informed context-appropriate equipment selection and procurement, specialized user and technician training, regular maintenance, the provision of appropriate spares and supplies, and on-going record-keeping, facilitates the sustainable use of concentrators in these contexts. Yet, in reality, implementing such an ecosystem remains a challenge, and documented evidence showing the effective long-term operation of such a system is scarce. For example, in both Malawi and Mongolia, on-going maintenance was identified as a major challenge, preventive maintenance was infrequent, and spare parts were either not available on site or the supply of parts was difficult to maintain [73].

The relatively successful use of oxygen concentrators at the MRC in The Gambia represents the potential that exists for BME departments in low-resource settings. The health technology management system in place has adequate resources for technician service training, a relatively reliable supply chain with strong manufacturer relationships, a budget for spare parts, tools, test equipment and regular maintenance, and capacity within the department to uphold and maintain a quality system [56, 97, 98]. In this section, we discuss what in our experience are four key elements of an oxygen concentrator support ecosystem and how the Unit has been able to successfully implement them. These elements are: (1) uniform context-appropriate equipment selection; (2) trained technicians and an established health technology management (HTM) program; (3) a system for routine preventive maintenance; and (4) resources for and access to spare parts.

1) Uniform, context-appropriate equipment selection:

Due to the harsh environmental conditions in many low-resource settings, the selection of concentrator models with appropriate specifications for these contexts is an important first step in ensuring long-term sustainability [102]. Several programmes which have implemented oxygen concentrators have recognized
the importance of identifying a suitable concentrator model for use in these contexts [33,42,86,91,105], some selecting models which, at the time of implementation, met the WHO's minimum specifications and performance criteria [145]. Due to low sales volumes and manufacturer take-overs, there are no longer any concentrator models on the market that meet these criteria. Recent surveys have compared the suitability of a range of concentrator models for use in tropical countries [102,103] in order to identify models with specifications as close as possible to the original WHO specification. The key message from these surveys has been that the selection of concentrators guided by technical issues is more important than selection by purchasing cost alone.

The MRC has made a strategic choice to standardize their oxygen concentrator technology with one manufacturer for ease of training, maintenance and parts replacement. This uniformity has likely played a role in the positive long-term performance of their concentrators. Since our analysis is limited to Airsep concentrators, we cannot draw any conclusions about the long-term performance of other makes or models in The Gambian context. The report by La Vincente et al. [73] suggests that the choice of concentrator is a major factor in long-term sustainability, with certain manufacturers showing poor performance in both the Malawian and Mongolian contexts after limited use. Although only two of the 62 concentrators from that study were by Airsep, both were found to be working well, one of them after 10,600 h of use [73]. In general, introducing different makes and models complicates training, up-keep, and maintenance, and thus uniformity of equipment should be encouraged [42,73,86].

2) Trained technicians and an established health technology management program:

Poor maintenance capacity is a major challenge for health systems in developing countries. The lack of trained professionals (either BMETs or biomedical engineers) who are able to execute needed repairs or maintenance is a common reported cause for medical equipment being out-of-service [80,81].

The MRC has a proven model for biomedical equipment maintenance and support in a low-income setting [97]. Support for oxygen concentrators was fully integrated into this existing system, rather than added on to the existing responsibilities of already burdened technicians. Repairs are assessed and delegated to appropriate staff who are then held accountable for their completion. As a result, equipment downtime has been kept to a minimum. All faults except for one were repairable in-house, and 85% of all machines ever put into service are still in use.

As evidenced by past oxygen-focused initiatives, providing oxygen concentrator-specific training at the outset of a project does not necessarily guarantee that there will be on-going concentrator support in the long-term. For example, although training and spares for on-going maintenance were supplied through the project in Malawi, the cost of engineering support was not included in the project budget because the Ministry of Health already funded vehicle, travel and personnel costs for regular maintenance visits by biomedical engineers [42]. Unfortunately, “many scheduled maintenance visits did not occur due to financial constraints within the electromedical engineering department” [42]. Similarly, in Mongolia it was reported that the budget allocation for the maintenance and repair of hospital equipment was insufficient [73]. Technical support for concentrators should be fully integrated into existing technology management systems, and if such systems are inadequate, resources should be allocated to improve the capacity of these systems in the long term.

Good record keeping is another essential component of an HTM program, however this has also proven to be challenging in other low-resource settings. Reliable records of the breakdown and repair
of equipment were not available for the programs implemented in Malawi or Mongolia [42, 73] making it difficult to determine common failure modes, or areas for improvement in the maintenance program. Record keeping at the MRC has been facilitated by a centralized electronic equipment management database. Although some work requests do originate on paper, ultimately, all work orders are entered into the computerized system, regardless of the field site. These digital records have made this analysis possible. Such records are essential for building a stronger evidence base for the reliability and performance of concentrators – and all medical devices – in such contexts, and can serve to inform the planning, monitoring and evaluation of programs involving medical technologies.

3) A system for routine preventive maintenance:

Directly linked to trained maintenance staff and an HTM system is the practice of routine preventive maintenance. In a study of 60 resource-poor hospitals across the developing world, only 10 hospitals reported having partial or complete preventative maintenance programs in place [80]. Yet, one of the most common problems faced by broken but repairable equipment in developing countries is related to a failure to complete preventive maintenance such as cleaning filters or recalibration [81].

Our analysis further supports the importance of routine preventive maintenance. Forty-one percent of faults needing repair were discovered during PM checks, which likely helped mitigate more serious or costly future break-downs and lengthy equipment downtime. Automated scheduling within the electronic equipment management system has helped the BME department ensure that work orders for preventive maintenance are created, assigned to BMETs, and completed within allotted time frames. As of 2009, PM completion rate has been a key performance indicator included in the department’s quality system monthly reporting. This further incentivizes that these essential checks occur on schedule. Even concentrators located at remote sites have received regular routine preventive maintenance checks.

We cannot infer to what degree the frequency of major breakdowns or equipment downtime might be increased if the MRC had no preventive maintenance program in place. However, with an average of just over three PM checks per machine per year, about 69% of concentrators in service go without needing a repair each year. Compared to the concentrator assessment by La Vincente et al. [73], where no evidence of routine preventive maintenance was reported in either Malawi or Mongolia, the number of concentrators working well in The Gambia seems to be proportionally higher.

The preventive maintenance required for oxygen concentrators is neither time consuming nor technically complex, and should be emphasized and monitored in any program promoting the use of concentrators in a low-resource setting.

4) Resources for and access to spare parts:

Our analysis provides a realistic projection of quantities of spare parts needed at the outset of concentrator purchases. The cost of spare parts will be manufacturer-dependent as highlighted in a recent survey [102]. In our case, Airsep estimates that spare parts would cost US $27 for the first 40,000 h of use [102] (approximately 4.6 years of continuous use), which is based on the assumption that only filters would need replacing. Based on our experience, where several more expensive parts have needed replacement, this estimate may not be realistic. Median hours of use to date has been only 6,267, yet the median spending per machine was approximately US $9.50. Furthermore, we observed
three compressor replacements before 20,000 h, suggesting that another manufacturer’s estimate that no technical maintenance should be required until the compressor is replaced after about 20,000 h [86] may not be realistic in this context either. This highlights the importance of collecting and reporting real-world data and experiences both for technology management and planning, as well as for providing useful feedback to manufacturers.

Access to spare parts at the MRC has been established through a long-standing relationship with the concentrator manufacturer, and through a reliable institutional procurement process. The BME department also maintains a centralized store of replacement parts, and so parts that are ordered upfront with any new device (e.g., filters) are kept in storage until needed. La Vincente et al. [73] found that spare parts were generally not available at the hospitals visited, except for a few hospitals in Mongolia that had spare internal filters. Peel and Howie [102] recommend that spare parts for at least 40,000 h of use be purchased at the outset. This will help mitigate spare part shortages due to delays in the procurement processes common in low-resource settings.

On-going challenges for concentrator sustainability

Two major challenges faced by the MRC’s BME department when it comes to concentrator up-keep are: user maintenance and equipment downtime. Ward-based user maintenance of concentrators is very simple (i.e., frequent washing of outside filters [73]) yet in our experience it is not routinely done. More work is needed to ensure that users understand the importance of these small preventive measures for the longevity of equipment. This could include working with other departments and healthcare administrators to make sure that user maintenance of medical equipment is part of the job description of clinical health workers. Although equipment downtime has been only 5% of all days in service, the MRC has still experienced prolonged individual concentrator downtimes, especially for concentrators located at other facilities. Slow responsiveness from the supplier when obtaining parts for broken-down equipment is sometimes a challenge, as well as delays in the procurement process for major part shipments (e.g., sieve beds, compressors, etc.). Having spares of such major parts on-hand, rather than placing an order when a breakdown occurs, could help mitigate these long delays. The downside however is that an initial financial outlay would be required. Our study has provided evidence for which parts tend to fail and how often, to help justify such planning decisions.

Study limitations

A recognized limitation of this study is the failure to include labour costs in the overall cost of oxygen concentrator maintenance. The time spent by technicians working on repairs was not recorded for all repairs, and thus we could only calculate an estimate of total labour time. Labour represents an important financial and human resource constraint in most low-income settings. The WHO and others are working to raise the profile of biomedical technologists as essential ‘human resources for health’.

We also recognize that ranking the difficulty of repairs was a coarse approach to looking at the level of experience or skill required to maintain concentrators. In a parallel study, we have mapped these repairs to the specific skills required to complete them, and have proposed a training programme for concentrators based on this mapping exercise [16].

Since hours of use data were not historically recorded when a concentrator repair was completed, we could only report failures in relation to concentrator age and not hours of use. Recognizing that age is not necessarily correlated with usage, this was a major limitation of this analysis. We have learned that
hours of use should be included in the notes prepared by technicians when completing repairs. As we continue to collect data, future work could include stratifying results based on model type (at present, most of the units are Intensity’s but this could change in the future as newer models become available).

We also recognize that pulse oximeters, flow splitters, delivery tubing and nasal prongs are other essential technologies that should always accompany oxygen concentrators in a clinical setting. A comprehensive evaluation of such devices was beyond the scope of this analysis but would be important to consider in future work.

3.1.6 Conclusion

We present the first-ever study of oxygen concentrator reliability in a low-income setting based on individual device maintenance histories. Our experience of oxygen concentrator use demonstrates that low failure rates and repair costs, and lifespans exceeding 5 years, are possible given a support framework that includes informed standardized equipment selection, trained technicians, routine preventive maintenance and record keeping, and access to spare parts. This was all achieved at low cost with a relatively low labour time commitment. Furthermore, we show that accurate records of the maintenance histories of medical devices can provide insight into the performance, reliability, repair/maintenance costs, and equipment downtime. This account of the effectiveness of the health technology management system in place in The Gambia is a useful addition to existing literature on the use of concentrators in low-resource settings and will be helpful for decision-makers and project planners interested in implementing oxygen concentrators in developing world health systems. User maintenance and equipment downtime remain challenges for the long term and cost-effective use of oxygen concentrators in low-resource settings.

3.2 An Evidence-based Approach to Developing a Training Programme for the Maintenance of Oxygen Concentrators in Low-resource Settings

This work has been previously published (full citation: Bradley, BD et al. An evidence-based approach to developing a training programme for the maintenance of oxygen concentrators in low-resource settings. Proceedings of the 8th IET Appropriate Healthcare Technologies for Low-Resource Settings Conference, London:UK, Sept 2014 [16]). It has been reproduced here without changes in sections 3.2.1 - 3.2.5. The authors retained copyright ownership of this work.

3.2.1 Abstract

Oxygen concentrators are an appropriate and low-cost technology for supplying medical oxygen in low-resource settings; however some maintenance and occasional repairs are required to optimise their longevity. Through a skill-mapping analysis based on historical concentrator repair logs, we identified 31 basic technician skills that would be sufficient for the repair of over 90% of observed oxygen concentrator failures as well as for routine preventive maintenance. Most of these skills are drawn from the library of Biomedical Technician Assistant skills developed by the Developing World Healthcare Technologies Lab and Engineering World Health. We use this skill-mapping analysis to propose an evidence-based training curriculum specifically tailored to the maintenance of oxygen concentrators in low-resource settings.
3.2.2 Introduction

Research by Duke University’s Developing World Healthcare Technologies (DHT) Lab in collaboration with Engineering World Health (EWH) suggests that as much as 66% of out-of-service medical equipment in developing countries can be put back into service by providing technicians with skills-based training in five key knowledge domains; plumbing, electrical, mechanical, motors, and power supplies [80]. Through an analysis of thousands of medical equipment repair requests, DHT and EWH developed a training curriculum for biomedical technician assistants (BTA) centred around 113 skills that fall under these five key bodies of knowledge [80]. A skill is defined as “the steps required to diagnose and execute a repair”, and can be taught to a secondary school graduate in two hours [80]. A library of these resources is available online at: http://library.ewh.org [32,44].

Oxygen concentrators are an appropriate and low-cost technology for supplying medical oxygen in low-resource settings [8, 40, 41, 102, 105]; however some maintenance and occasional repairs are required to optimise their longevity. Concentrator upkeep is a challenge in settings with inadequate resources for maintenance [73].

In previous work, we analyzed almost 7 years of maintenance and repair data for 27 oxygen concentrators managed by the Biomedical Engineering Department at the Medical Research Council (MRC) Unit in The Gambia, and determined common failure modes, replacement parts needed, equipment downtime, expected useful lifespan, and annual repair costs [18]. The dataset of 808 electronic work orders from September 2006 to August 2013 consisted of 142 inventory inspections, 33 repairs, and 633 preventive maintenance checks (23 of which uncovered faults requiring corrective action). The 33 repairs and 23 corrective maintenance jobs were categorized by cause of failure (Table 3.1). The most common repairs were filter and check valve replacements, and leakages or faulty tubing.

Table 3.1: Frequency of different causes of failure for 27 oxygen concentrators (Sept 2006 to Aug 2013).

<table>
<thead>
<tr>
<th>Categories of cause of failure</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter needs replacement</td>
<td>8</td>
</tr>
<tr>
<td>Battery needs replacement</td>
<td>2</td>
</tr>
<tr>
<td>Faulty oxygen outlet</td>
<td>4</td>
</tr>
<tr>
<td>Leakage or faulty tubing</td>
<td>6</td>
</tr>
<tr>
<td>Faulty valve(s)</td>
<td>8</td>
</tr>
<tr>
<td>Pressure regulator needs adjustment</td>
<td>1</td>
</tr>
<tr>
<td>Electrical connection problems</td>
<td>5</td>
</tr>
<tr>
<td>Faulty flowmeter</td>
<td>3</td>
</tr>
<tr>
<td>Faulty sieve bed(s)</td>
<td>3</td>
</tr>
<tr>
<td>PCB problems or failure</td>
<td>2</td>
</tr>
<tr>
<td>Compressor problems or failure</td>
<td>1</td>
</tr>
<tr>
<td>Multicomponent failure</td>
<td>8</td>
</tr>
<tr>
<td>Unknown</td>
<td>5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>56</strong></td>
</tr>
</tbody>
</table>

A mean of just over three preventive maintenance checks were completed per machine per year. Preventive maintenance involves testing the oxygen concentration, cleaning the interior, checking batteries, and inspecting internal filters. Over the 7-year analysis period, 85% of concentrators experienced two
or fewer repairs. Mean time to the first failure was over two years. In any given year, about 30% of concentrators in service experienced a failure [18].

Based on this previous analysis, we hypothesize that a very basic set of skills would be sufficient to repair the most common causes of oxygen concentrator failure. The BTA skill library developed by DHT and EWH offers a starting point to test this hypothesis. In this paper we present the results of a skill-mapping exercise that maps each reported concentrator failure to the specific skills needed to complete the repair. We also propose an outline with key topic areas for an evidence-based training program for concentrators. Lastly, we estimate the percentage of concentrator repairs that could be resolved with this evidence-based training approach, and note those repairs requiring a higher skill level or more advanced knowledge that do not fall under this skills-based curriculum.

3.2.3 Methods

Seven of the 56 reported repairs [18] were excluded from this analysis; five had unknown or unrecorded causes of failure, one failed beyond repair, and one was still unresolved at the time of analysis. We mapped the remaining 49 repairs to specific skills needed to resolve them, drawing upon the DHT-EWH BTA skills library [44] where appropriate. For example, the replacement of filters was one of the most common repairs we observed, which is a skill under the “Plumbing” knowledge domain. Additional skills not found in this library were noted. We also identified the BTA skills needed to perform routine preventive maintenance.

All MRC concentrators are from AirSep (Buffalo, NY) and thus have uniform skill requirements. The skills needed for some repairs could depend on the specific concentrator make and model (e.g. type of clamp used for tubing). Based on our knowledge of other makes and models we included a range of related skills so that our analysis applies generally across all concentrator types.

3.2.4 Results

Skill-mapping analysis

As shown in Table 3.2, 24 unique skills from the BTA skills library [44] were mapped to 49 oxygen concentrator repairs. The number of times each skill was mapped to a repair is indicated in parentheses.

Additional skills not found in the BTA library that we believe were necessary for concentrator repairs are outlined in Table 3.3. One essential additional skill was pressure testing using a pressure gauge (assuming the tool is available). Pressure tests should be completed after any repair involving valves, leakages, tubing, flowmeters or the pressure regulator. Most concentrator models currently on the market are equipped with an oxygen sensor and alarm that is triggered if the output concentration drops below a certain threshold. In our experience, this alarm only failed once (one of the multicomponent failures), but it is important to be able to repair this vital component. Sieve beds are a component unique to oxygen concentrators that require special gripping tools to remove. For printed circuit boards (PCB), we added a skill for advanced PCB troubleshooting, but these failures were rare in our experience (Table 3.1). In the analysis by DHT [80], such advanced repairs were classified as “Other”. With the exception of the advanced PCB skill, we believe the additional skills in Table 3.3 are similar in difficulty level to those in the BTA curriculum (i.e., could be taught to a secondary school graduate in two hours).

Eighteen (37%) repairs were completely resolved using only BTA skills, and 28 (57%) repairs were resolved with a combination of BTA skills and basic non-BTA skills from Table 3.3. The other three
Table 3.2: List of 24 BTA skills that were mapped to 49 concentrator repairs, with frequency in parentheses.

<table>
<thead>
<tr>
<th>Knowledge Domain</th>
<th>Knowledge Unit</th>
<th>Skills (number of occurrences)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electrical</td>
<td>Connections</td>
<td>• Building and using a continuity tester (8)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Desoldering (8)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Selecting wire (3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Soldering (8)</td>
</tr>
<tr>
<td>Mechanical</td>
<td>Attachment</td>
<td>• Tools for adjusting bolts and screws, choosing different heads (8)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Super glue/glue (7)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Zip ties (17)</td>
</tr>
<tr>
<td></td>
<td>Cleaning</td>
<td>• Using a damp cloth (1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Cleaning inside of things (1)</td>
</tr>
<tr>
<td>Motors</td>
<td>Tightening, attachment, balance</td>
<td>• Mounting motors (3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Vibration problems (3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Set screws (3)</td>
</tr>
<tr>
<td></td>
<td>Belts, gears, shafts, coupling</td>
<td>• Bent shaft (vibration and wobbling) (3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Loosen, tighten, low power (3)</td>
</tr>
<tr>
<td></td>
<td>Cleaning and lubrication</td>
<td>• Squealing, grinding, overheating, foreign objects (3)</td>
</tr>
<tr>
<td>Plumbing</td>
<td>Blockage</td>
<td>• Cleaning valves and tubes (1)</td>
</tr>
<tr>
<td></td>
<td>Connections</td>
<td>• Clamps (21)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Hose barb with screw clamps (11)</td>
</tr>
<tr>
<td></td>
<td>Filters</td>
<td>• Cleaning (and inspection) (10)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Substitution (10)</td>
</tr>
<tr>
<td></td>
<td>Leakage</td>
<td>• Cutting tubes (1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Finding holes/leaks (20)</td>
</tr>
<tr>
<td></td>
<td>Seals</td>
<td>• O-rings (4)</td>
</tr>
<tr>
<td>Power supply</td>
<td>Batteries</td>
<td>• Substituting primary batteries (5)</td>
</tr>
</tbody>
</table>

repairs (one of which was a multicomponent failure) required the advanced PCB skill. No repairs required an entirely different skill set.

A mean of 4.0 ± 2.3 skills were needed per repair. Multi-component failures required more skills (mean 6.7 ± 4.2). Plumbing and mechanical skills were used the most, however competency across all knowledge domains was needed. Twenty-five (51%) repairs required skills from two or more domains.

Nine skills are needed to perform routine preventive maintenance for concentrators (Table 3.4). All BTA skills for preventive maintenance except for calibration and cleaning using compressed air were also mapped to repairs (Table 3.2). The calibration skill describes how to test oxygen concentration in the absence of an oxygen analyser. We also added the basic skill “using an oxygen analyser” as this test equipment may be available in some settings.

We were unable to explicitly address the issue of diagnosis in this analysis. All the failures analysed were diagnosed and repaired by MRC biomedical engineering technologists (BMETs) with college-level electronics backgrounds. We had no record of the steps taken to troubleshoot issues and recommend repair solutions. That being said, based on failure descriptions and repair notes, we estimate that 63%
(31) of the failures were likely diagnosable using BTA skills only. For example, of the 31 diagnosable failures, the following BTA diagnosis skills were mapped in our analysis (frequencies in parentheses): how to find holes and leaks (7), checking if a battery is dead (4), checking if a filter is dirty (8), and using a continuity tester (for testing circuits) (4). Other physical issues (e.g., faulty flowmeter (3), outlet requiring re-attachment (4), or a pinched tube (1)) were likely diagnosable upon visual inspection. Recognizing that diagnosing a cause of failure can be more challenging than the repair itself, diagnosis is included as a topic in our proposed training programme.

Table 3.3: List of skills not in BTA library that were mapped to concentrator repairs, with frequency in parentheses.

<table>
<thead>
<tr>
<th>Knowledge Domain</th>
<th>Basic or Advanced</th>
<th>Skill (number of occurrences)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electrical</td>
<td>Basic</td>
<td>Testing and replacing alarms and buzzers (1)</td>
</tr>
<tr>
<td></td>
<td>Advanced</td>
<td>Advanced PCB trouble-shooting and component selection (3)</td>
</tr>
<tr>
<td>Mechanical</td>
<td>Basic</td>
<td>Using special gripping tools (for replacing sieve beds) (4)</td>
</tr>
<tr>
<td></td>
<td>Basic</td>
<td>Pressure testing using a pressure gauge (20)</td>
</tr>
<tr>
<td></td>
<td>Basic</td>
<td>Removing old glue (4)</td>
</tr>
</tbody>
</table>

Table 3.4: BTA and non-BTA skills required for preventive maintenance of oxygen concentrators.

<table>
<thead>
<tr>
<th>Knowledge Domain</th>
<th>Knowledge Unit</th>
<th>Skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mechanical</td>
<td>Attachment</td>
<td>Tools for adjusting bolts &amp; screws, choosing different heads</td>
</tr>
<tr>
<td></td>
<td>Calibration</td>
<td>Oxygen concentrator</td>
</tr>
<tr>
<td></td>
<td>Cleaning</td>
<td>Compressed air</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Using a damp cloth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cleaning inside of things</td>
</tr>
<tr>
<td>Plumbing</td>
<td>Blockage</td>
<td>Cleaning valves and tubes</td>
</tr>
<tr>
<td></td>
<td>Filters</td>
<td>Cleaning (and inspection)</td>
</tr>
<tr>
<td>Power Supply</td>
<td>Batteries</td>
<td>Substituting primary batteries</td>
</tr>
</tbody>
</table>

**Additional basic skill not in BTA list**
- Testing O₂ concentration using an oxygen analyser

Proposed training curriculum

As a result of this analysis, we propose that an oxygen concentrator-specific training curriculum should include the following topic areas:

- Overview of the functionality of concentrators, and their use in clinical settings
- Overview of the main components of a concentrator
- Overview of common concentrator failures and strategies for diagnosis (based on results from [18])
- Concentrator Skills Training

3.2.5 Discussion

The proposed training curriculum for oxygen concentrators would be sufficient for both routine preventive maintenance and the repair of over 90% of concentrator failures. A key component of this curriculum is a set of 31 basic skills that have been identified based on evidence of commonly observed concentrator failures and preventive maintenance needs. These skills could be taught to a secondary school graduate in about 2 hours each [80]. Twenty-six of these skills are part of the evidence-based curriculum designed for BTAs by the DHT Lab and EWH, which has demonstrated positive results in Rwanda [82].

Repairs that do not fall under this training approach are electrical failures related to PCBs that require more advanced knowledge to diagnose and repair. In our sample of repairs we only observed three such repairs over a 7-year period. Since all MRC technicians have a college-level electronics background, these repairs were manageable in our setting.

All of the BTA knowledge domains were relevant to oxygen concentrators, although the context is slightly different for some bodies of knowledge (e.g., plumbing skills would be applied to pneumatics, and motor skills applied to compressors). There may be other BTA skills not listed in Table 3.2 that are relevant to concentrators, however they were not required for any of the repairs analysed.

We did not explicitly address the issue of diagnosis, which can often be more challenging than the steps required for the repair itself. However, we believe over half of the concentrator failures would have been simple to diagnose, and several BTA skills related to failure diagnostics were included in the mapping exercise. Diagnosis does not appear to be a major barrier to the maintenance of concentrators.

Our analysis indicates that some device-specific training is necessary in order to cover repairs for all observed failure modes; for example, the handling of sieve beds, and checking the pressure and oxygen concentration during preventive maintenance and after repairs. The BTA curriculum does not assume any theoretical knowledge of the principles of operation of a device, but we felt it important to add such topics in our proposed training curriculum.

One might debate the validity of device-specific training versus a more comprehensive approach to BMET training for a wide range of devices and potential modes of failure. However, global health interventions are often targeted at a specific illness or treatment method, and along with this comes the mass-installation of a specific medical device, concentrators being a good example [42,86]. An evidence-based, device-specific training program could serve to supplement or refresh existing BTA or BMET...
skills when such a program is introduced to ensure that already time- and resource-constrained health technology management programs can adequately support the new equipment.

There is a growing recognition in the global health community that task shifting of healthcare professionals could improve efficiency and relieve financial pressures on resource-constrained health systems [49]. We hope the analysis presented herein may contribute to this dialogue for the profession of biomedical engineers and technologists, demonstrating that a substantial portion of maintenance needs for simple, low-cost technologies like oxygen concentrators, could be shifted to lower skilled BTAs so that BMETs are freed up for more technically complex diagnosis and repairs, and other tasks related to health technology management. Other medical devices similar in complexity to concentrators where this could apply include: scales, blood pressure devices (sphygmomanometer or non-invasive electric), nebulisers, or simple mechanical ventilators and CPAP machines.

We acknowledge that having highly-skilled BMETs is crucial for the management and scheduling of repairs and maintenance, and for ensuring that quality is maintained. However, evidence shows that most oxygen concentrator repairs require a low skill level, and that simple preventive maintenance for concentrators can be delegated to assistant BMETs – or BTAs – who have been taught the appropriate skills. A skills-based approach to technician training, such as that offered by the DHT and EWH, could significantly contribute to the long-term maintenance and longevity of oxygen concentrators in low-resource settings where some level of BMET support is available.

A limitation of this analysis is the small sample size of repair work orders mapped to skills, however, the time period over which these repairs took place was longer than any previous assessment of concentrator functionality. To our knowledge, no assessment of the skills required for repairs and maintenance based on real-world data has ever been conducted for oxygen concentrators. This represents an important step in understanding concentrator maintenance needs and the experience and skill level required to maintain this life-saving technology in the long-term.

3.2.6 Conclusion

A skills-based approach to technician training in a low-resource setting, such as that proposed in this paper or more broadly by DHT and EWH, would be highly effective for the repair and maintenance of oxygen concentrators, which are simple, low-cost medical devices. Concentrator failures are not very complex, and the knowledge required for repairs can easily be taught to qualified people within a reasonable amount of time. Our proposed evidence-based training curriculum includes important device-specific topic areas in addition to basic skills in order to provide a comprehensive overview of concentrator operation, maintenance and repair.

3.3 Chapter 3 Design Implications for the OxOpt Model

This section describes specific OxOpt model design considerations and features that are based on the data and analyses from this chapter. A summary of these model features is provided in Table 3.5.

The first design feature is the Concentrator Module of the Technology Systems Model (TSM) (section 7.2.2), which simulates the frequency of oxygen concentrator repairs and equipment downtime at the health facility-level. Probability distributions for time between failures and time to complete a repair (i.e., equipment downtime) were determined from the analysis of section 3.1 [18] using Stat::Fit (Geer Mountain Software Corp, South Kent, CT). Any repair whose work order was opened and closed on the
same day was assumed to have a downtime of two hours (i.e., the labour time allotted to complete a repair in the OxOpt model). Time between failures (hours) was log-normally distributed, with \( \mu = 9.4 \) and \( \sigma = 0.8 \), which has a mean of about 16,500 hours (or 685 days). Time to complete a repair (hours) was exponentially distributed, with \( \beta = 1810 \), although this was not as strong of a fit due to a couple of outliers in the > 9000 hours range. More details including formulas and figures for the probability density functions of these two random variables are provided in Appendix B.

Second, the model incorporates resources for sustaining the equipment support ecosystem described in this chapter (section 3.1.5). There is an implicit assumption that this equipment support ecosystem is achievable in the setting of interest and is sustainable in the long term. It is also assumed that technicians already employed by the Ministry of Health in the country being modeled are available to be trained for the purposes of maintaining oxygen concentrators. However, technicians do not necessarily need to be posted at every health facility. Provisions are in the model for the cost of technicians to travel to facilities that do not have a permanent technician on-site.

In terms of uniform and context-appropriate equipment selection, the only oxygen concentrator recommended in the OxOpt model is the Airsep Elite, which had the highest ratings in independent studies evaluating different oxygen concentrators against criteria relevant for low-resource settings (e.g., cost, operation at 40°C, 95% rH, etc.) [102, 103]. The Elite supplies oxygen at 5 L/min and consumes 350W. The default capital cost \( (c) \) of US $1,025 is based on the most recent purchasing data from The Gambia, but this is a user-defined input parameter that can easily be changed based on the context. A 5-way flow-splitter is considered a required component with each concentrator purchase as well (see section 4.3 for details on oxygen system components). The expected lifespan for concentrators is conservatively set to 5 years, but this is also a user-defined parameter.

Training for both health care workers and technical staff is an essential component of the support ecosystem. The OxOpt model incorporates cost estimates for initial user and technician training at the outset of an oxygen project, as well as annual refresher training to keep technicians up to date and to help deal with the challenges of high staff turnover. The initial training course could be conducted in one location, bringing all relevant stakeholders to a central location, or could be repeated on a smaller scale in multiple locations. Regardless of the approach, the overall budget for initial training is set to US $1,000 per concentrator installed. The cost estimate is determined by the number of concentrators so that it scales with the size of the project and thus the effort involved in training all necessary staff. For example, if the model was run for a whole health district and it was determined that 10 concentrators were needed, US $10,000 would be budgeted for training (regardless of how those concentrators were allocated across the district), whereas if the model was run for just one major hospital requiring two concentrators, US $2,000 would be allocated.

This approach to estimating initial training costs was verified with an expert in technician training, specifically on oxygen concentrator maintenance, and is consistent with the budget allocated for training in other studies when calculated on a per-concentrator basis (e.g., US $1,225 in Malawi [42] and US $970 in Papua New Guinea [41]). It is believed this estimate is sufficient to cover a 62-hour training program (i.e., the estimated time required to cover the 31 skills needed to repair concentrators as shown in section 3.2 [16,80]). It is also assumed that training for any additional equipment required (e.g., battery or solar equipment) could be incorporated into the basic concentrator training plan at minimal additional cost. For example, Schneider et al. [118], who set up a solar-powered concentrator in The Gambia, reported that training for solar panel maintenance duties could be achieved in a 1-day workshop.
Although the programs in Papua New Guinea and Malawi budgeted for follow-up monitoring visits, they did not include a budget for on-going refresher training for technicians. This cost is built into the OxOpt model on a per health facility per year basis. In practice, this budget allotment could be pooled to provide a centralized annual refresher course in one location.

The model also incorporates resources for routine preventive maintenance and repairs. The cost to perform three PM checks per concentrator per year, at 30 minutes of labour time per check, is included in the system operating costs. For each concentrator failure that occurs based on the random timing described above, the mean cost of repair observed in The Gambia (US $55) [18] is added to the operating costs. Additionally, the model considers whether or not a technician is locally available, and works in costs for the transport of a trained technician from elsewhere to complete necessary repairs.

With this basic support in place, the model assumes that the concentrators will experience similar failure frequencies, downtime, and lifespans as those observed in The Gambia [18]. Note that in settings where resources are not allocated to supporting equipment maintenance and on-going training, then it cannot be assumed that the same frequency of failures, downtime, and lifespan would occur. The model would have to be adjusted to reflect poorer performance over time.
Table 3.5: OxOpt model design features and parameters based on analyses in Chapter 3.

<table>
<thead>
<tr>
<th>Model Parameter</th>
<th>Default Value</th>
<th>Notes and source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time between failure (hrs)</td>
<td>min = 0, μ = 9.4, σ = 0.8</td>
<td>Random variable: ~ lognormal(min, μ, σ); Bradley et al. (2015). See Appendix B.</td>
</tr>
<tr>
<td>Time to complete repair (i.e., equipment downtime) (hrs)</td>
<td>min = 2, β = 1810</td>
<td>Random variable: ~ exp(min,β); Bradley et al. (2015). See Appendix B.</td>
</tr>
</tbody>
</table>

Cost and other parameters related to Equipment Support Ecosystem

1) Uniform and context-appropriate equipment selection

- Concentrator make and model: Airsep Elite 5 L/min; Peel et al. (2009, 2013)
- Capital cost of concentrator ($US): 1025
  - MRC purchasing records, includes shipping
- Capital cost of 5-way flowsplitter ($US): 625
  - MRC purchasing records, includes shipping
- Estimated concentrator lifespan (yrs): 5
  - Median age in The Gambia: 6.1 years [IQR: 3.3, 6.9], Bradley et al. (2015)

2) Trained technicians and an established health technology management program

- Initial user and technician training cost, per concentrator installed ($US): 1000
  - Total training budget estimated based on number of concentrators to be installed (i.e., will scale with size of solution). Default value based on consultation with experts, and Duke et al. (2008), Enarson et al. (2008)
- Refresher user and technician training cost, per health facility per year ($US): 200
  - Based on consultation with experts
- Technician labour cost, per hour ($US): 1.4
  - Based on consultation with MRC BMETs

3) A system for routine preventive maintenance

- Frequency of preventive maintenance (PM), per concentrator per year: 3
  - Bradley et al. (2015)
- Hours of labour per PM check: 0.5
  - Bradley et al. (2015), based on consultation with MRC BMETs

4) Resources for and access to spare parts

- Mean cost per repair ($US): 55
  - Bradley et al. (2015)
- Hours of labour per repair: 2
  - Bradley et al. (2015), based on consultation with MRC BMETs
- Cost of technician transport per repair ($US): 20
  - For health facilities without onsite maintenance capacity, based on consultation with MRC BMETs

TSM = Technology Systems Model; MRC = Medical Research Council, The Gambia; BMET = Biomedical engineering Technologist. * If parameter is a user-defined input; otherwise, parameter is a built-in feature of the model. See section 7.3 for all OxOpt model parameters; † User can edit these values to suit the specific application; ‡ See section 7.2.2 for details on the Concentrator Module of the TSM.
Chapter 4

Supply Side (Part II): Alternative Energy Options for Oxygen Concentrators

4.1 Introduction

In order to reap the benefits of unlimited oxygen afforded by oxygen concentrators, alternative energy sources such as batteries and photovoltaics need to be explored to compensate for the unreliable grid supply affecting many low-resource settings. A major part of this research has been to conceptualize, compare, and in some cases, field test such systems. This chapter is the synthesis of four conference papers [17, 22–24] and one journal paper [21], all describing conceptual work and field experience from The Gambia related to alternative energy sources for concentrators and other oxygen backup systems. I was the lead and first author on all of these papers, but they were a collaborative effort with colleagues at the Medical Research Council (MRC) Unit, The Gambia.

The three main alternative energy options considered in this chapter are uninterrupted power supply (UPS), grid-charged battery backup, and solar-powered systems, although oxygen storage systems, generator backup and cylinder oxygen have also been explored as part of this research. At present, there are no revolutionary oxygen technologies for medical use under consideration for ISO standardization; thus the oxygen systems considered here are currently the best available for this context. The aim and scope of this work is not to evaluate new technologies but to evaluate in a more effective way existing technologies in new configurations that are appropriate for low-resource settings.

In Bradley et al. (2011) [17], the design and bench-testing of a grid-charged battery backup system are presented. This system, which was installed for field testing at a health facility in The Gambia in 2011 [22], was designed to power a concentrator 24/7 with as little as four hours of grid electricity per day. In Bradley et al. (2012) [24], a computer model was developed to compare the cost-effectiveness of storing energy (e.g., in batteries) versus storing concentrated oxygen (e.g., in a reservoir) in settings with limited or unreliable power. Battery backup and solar-powered energy storage systems\(^\text{1}\) were compared to commercial and non-commercial (i.e., pieced together from available components) oxygen storage

\(^{1}\)Note: UPS was not considered in this analysis
systems. It was concluded that for both low and high levels of grid availability, energy storage systems were preferable in terms of initial capital cost and cost per 1000 L of oxygen produced.

In parallel work [23], energy storage and oxygen storage systems were compared against less quantifiable but equally relevant criteria specific to low-resource settings – i.e., feasibility, sustainability, technical complexity, maintainability, usability, and adaptability – using a relative ranking framework. Based on this evaluation, grid-charged battery backup systems were the most favourably ranked option and non-commercial storage systems were the least favourable option.3

Most recent was a follow-up study of a UPS backup system installed at the MRC hospital in 2004 [21]. This retrospective analysis reported on system functionality and cost 8-years post installation, the longest follow-up study of a concentrator-based system to date.

The remainder of this chapter is structured as follows. Section 4.2 provides background on the status of grid electricity availability across much of sub-Saharan Africa and the need for alternative energy options in health care settings. In section 4.3, different alternative energy options are explored. Rather than present published papers sequentially and in their entirety [17, 21–24], this section is grouped by energy system type (e.g., battery-powered, solar-powered, etc.) and draws upon paper content in the following subsections: system overview, experience from the field, and maintenance and cost. Section 4.4 summarizes how this work has informed aspects of the OxOpt model design; specifically, which alternative energy options to include in the model, and a decision tree guiding the choice of the most appropriate alternative energy system for a given health facility.

### 4.2 Electricity Availability in Sub-Saharan Africa: The need for alternative energy sources

Access to electricity is critical to healthcare delivery [1]. Without electricity, many essential technologies cannot operate and important health care interventions, such as oxygen therapy via concentrators, simply cannot be provided. Lack of access to electricity is a problem in much of the developing world. A recent systematic review of 11 countries and 4,640 health facilities across sub-Saharan Africa found that on average 26% of health facilities have no access to electricity (range 0 – 58%), and that only 28% of those facilities with electricity reported reliable access (range 15 – 49%) [1]. In general, detailed data on electricity availability in low- and middle-income countries are scarce, which means this barrier to effective healthcare delivery is not well understood. Better data are needed for planning alternative energy options for medical devices.

In The Gambia, a 2009 survey of 12 health facilities found that electricity availability varied considerably across the country. The majority of facilities (seven) had power for less than 12 hours per day, but two had 12 to 19 hours and three had nearly 24 hours of power per day [61]. Intuitively, the choice of alternative or backup energy supply would be very different in these different settings, but without more specific data about patterns in availability those decisions would be difficult to make.

For this thesis, empirical data were collected in seven Gambian health facilities between 2009 and 2011 to better understand trends in electricity availability in this setting; data for three of these facilities

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2Cost estimates at the time of analysis were based on experience in The Gambia with purchasing various system components.

3Note: UPS was not considered in this analysis.

4In this survey “reliable access” meant power available during all regular service hours, with no outages exceeding 2 hours on a given day in the week prior to data collection [1].
were previously published [17]. Results for all seven facilities are provided in section 8.2.3 as part of the situational analysis for The Gambia case study.

The following section outlines the alternative energy systems considered for powering oxygen concentrators in low-resource settings with unreliable electricity, and the contexts in which each are most appropriate.

4.3 Options for Alternative Energy Systems

For health facilities that experience unexpected interruptions, an appropriate alternative energy source should provide continuity of electricity supply throughout frequent short interruptions, as well as less frequent but longer interruptions. For facilities with expected (i.e., scheduled) grid blackout periods, the backup supply must compensate for interruptions of known duration as well as possible unexpected interruptions.

Although electricity availability is the main consideration when choosing an appropriate alternative energy option, one must also consider other attributes, limitations, available field experience, cost, and training and maintenance needs of these technologies. All of the systems described herein will require some minimum level of maintenance and technical know-how for installation. Only the maintenance needs for system components external to the oxygen concentrator will be discussed below. A detailed analysis of training and maintenance needs for oxygen concentrators was presented in Chapter 3.

General system configurations are presented without specific component details. It is beyond the scope of this thesis to evaluate or recommend specific makes and/or models of system components, however independent analysis has shown Airsep oxygen concentrators (Chart Industries, Buffalo, NY) to be the most appropriate commercially available concentrators for tropical and low-resource settings [102,103]. All of the system diagrams below depict a concentrator connected to a flow-splitting assembly (e.g., Sureflow by Airsep) with two inputs and five adjustable output flowmeters, which can be connected to tubing to supply up to five children simultaneously at precise titrations of 0.1 to 2 L/min. Oxygen concentration should be greater than 82% at all times [152].

Cylinder oxygen is likely not cost-effective as the primary oxygen source in most low-resource settings [34, 63, 76, 91, 105], and may not be available in all settings. But where available, cylinders can be connected to the second input on the flow-splitting assembly as a backup oxygen source [152]. In the event that the concentrator should cease to operate or the alternative energy source has failed, manually switching over to the cylinder oxygen supply would simply involve opening the cylinder via the regulator, a task most users would be familiar with, supplying an alternative flow to the flow-splitting device. A backup supply of two 6000 L cylinders continuously supplying 5 L/min would last almost two days. Additional backup cylinders can be added for a greater buffer time if needed.

4.3.1 UPS system: Good electricity availability

System overview

A UPS dedicated to oxygen concentrators is an appropriate solution for settings where power interruptions are frequent but short in duration (i.e., less than 2 hours) [21]. Patient ward(s) requiring oxygen can be fitted with wiring and electrical outlets such that concentrators are plugged directly into the UPS supply (Fig. 4.1), which automatically and seamlessly provides continuity of power to those outlets.
in the event of a grid power outage. One of the main advantages of this setup is that from the user’s perspective (e.g., a nurse or physician), no intervention is required in the event of a power outage [21]. An added benefit of the UPS is that it provides consistency of voltage when mains or generator supply are of poor quality.

The UPS capacity should be chosen to suit the specific application requirements. For example, a typical 8.0 kVA UPS can support one 590W concentrator for about 100 min or five concentrators (mix of 350W and 590W) for about 23 min [21]. System attributes and limitations are summarized in Table 4.1.

Evidence in the field

In 2004, the MRC Unit in The Gambia implemented a UPS system for oxygen concentrators in their 42-bed hospital to replace cylinders as their main source of oxygen. This hospital has electricity from the national grid and back-up generators, but suffers power interruptions several times a week, typically of a few minutes up to about half an hour. During a monitored period from November 2011 to September 2012, on average about 15 interruptions per week were recorded, with mean interruption duration of about 1 min, and a maximum recorded interruption of 38 mins [21].

The UPS system was still successfully supplying power to concentrators 8-years post-installation. The system required only minimal maintenance over the 8-year period, and it was estimated that oxygen was supplied at 49% of the cost of cylinder oxygen [21]. Furthermore, users felt the concentrator-UPS system was safer than the hazards of moving large cylinders, logistically simpler than cylinders, easier to use, and provided greater confidence that oxygen supplies will never run out [21].

Maintenance and cost

Based on experience in The Gambia, a UPS system is expected to require very little maintenance, apart from the regular maintenance required for oxygen concentrators, which includes periodic cleaning, filter replacements, and minor repairs (see Chapter 3). The MRC Unit has in-house biomedical engineering
and facilities support for the maintenance of concentrators and the UPS, including routine preventive maintenance and access to spare parts. At the 8-year assessment, the original UPS was still in service, and no major parts had required replacement during the first two years of operation [21].

The system in The Gambia is the only known example of a UPS-oxygen concentrator setup. The cost of the UPS unit (8 kVA in this case) was estimated to be US $8,100, including installation and wiring costs. This unit was servicing three patient wards and may be oversized for many settings, especially where the wards are not in close proximity and cannot share one UPS unit. The total 8-year system cost, including electricity, maintenance and the capital cost of the UPS and 14 concentrators, was estimated to be about US $45,850, or US $2.74 per 1000 L produced, a savings of over 50% compared to cylinder oxygen [21].

Table 4.1: Attributes and limitations of UPS backup oxygen delivery system.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>• All components readily available; one system has been assembled in The Gambia.</td>
<td>• Only appropriate in settings with very short power interruptions (&lt; 2 hours)</td>
</tr>
<tr>
<td>• Can be integrated into a health facility ward such that health workers interface with concentrators and flowmeters only, by wiring sockets directly to the UPS in another room (as demonstrated in The Gambia).</td>
<td>• Initial capital investment is relatively high (from US $4,000 to US $8,000 depending on how many concentrators are connected).</td>
</tr>
<tr>
<td>• In the event of a power outage, no user intervention is required and there is no interruption in oxygen supply.</td>
<td>• UPS electrical sockets designated for concentrator use only may be subject to misuse in the event of a power outage unless properly monitored.</td>
</tr>
<tr>
<td>• Minimal maintenance required.</td>
<td></td>
</tr>
<tr>
<td>• Components expected to last at least 5 years (8 years shown in The Gambia).</td>
<td></td>
</tr>
<tr>
<td>• Operating costs are relatively low.</td>
<td></td>
</tr>
<tr>
<td>• Consistency of voltage provided by the UPS will help prolong the life of concentrators.</td>
<td></td>
</tr>
</tbody>
</table>

* Bradley et al., (2016) [21]

4.3.2 Grid-charged battery backup system: Moderate electricity availability

System overview

A grid-charged battery backup system is an appropriate solution where grid interruptions are frequent and expected to be longer than two hours a day (i.e., where a UPS solution would not be appropriate) [24]. Such a system consists of a battery bank, a charger, and a DC-to-AC inverter (Fig. 4.2). The charger is plugged into a grid power outlet. The batteries recharge when grid power is available and discharge when there is no power and the oxygen concentrator is in use. Since the concentrator draws power directly from the battery bank via the inverter, the system automatically and seamlessly switches to battery discharge mode in the event of a power outage [17,23]. Deep-cycle batteries are beneficial because they are designed to be discharged as much as 80% (with the ideal depth-of-discharge (DOD) being 50%) without affecting their useful lifespan [17].

In theory, each of the components in this system should be individually scaled to suit the specific application requirements. For example, battery capacity should be chosen according to the typical power interruption duration such that batteries will not be depleted below an ideal DOD of 50% [22].
charger capacity would be chosen such that the required charge can be stored in the batteries using the available grid electricity per day.

Similar to the UPS system, one of the main advantages of the system as presented in Fig. 4.2 is that from the user’s perspective (e.g., a nurse or physician), the oxygen concentrator operates exactly as how one would expect it to. In the event of a power outage, since the system is connected directly to the battery bank via the inverter, no intervention is required on the part of the user. The concentrator is essentially plugged into a reliable supply of electricity 24 hours a day, 7 days a week, irregardless of the grid supply. Furthermore, the quality of the voltage supplied to the concentrator from the inverter is typically better than the grid supply itself, which is beneficial for the lifespan of the oxygen concentrator in the long run. System attributes and limitations are summarized in Table 4.2.

Evidence in the field

There is limited published evidence of the use of batteries as a backup power source for oxygen concentrators. One reported field case used a 45-amp car battery for a single concentrator in Nigeria, but sustainability of the system was not described [91]. In 2009, a battery backup power system was developed in The Gambia that was specified to operate a 350W concentrator continuously for 24 hours with as little as four hours of grid charging time per day, which represents the expected worst case scenario in this setting. The system consisted of a bank of eight 6V, 350Ah gel sealed valve-regulated lead-acid (VRLA) deep-cycle, maintenance-free batteries. Results of bench testing at the MRC Unit were previously reported in Bradley et al. (2011) [17]. It was shown that the system performed well under typical electricity conditions for Gambian health facilities (see section 8.2.3), and that power interruptions of 2 hours or less had very little effect on the overall charge of the system. It was also shown that available grid charging time could be either consecutive hours or dispersed throughout the day. For all experiments, oxygen concentration was consistently over the required minimum ($\geq 85\%$) regardless of the input power source [17].
In July 2011, the system was installed to serve the paediatric ward at the Basse health centre in rural Gambia (see Fig. 4.3) and was still in use as of 2016. The batteries, charger, and inverter were isolated in an adjacent well-ventilated room. New wiring was installed to connect outlets designated for concentrator use only in the paediatric ward to the battery system.

![Grid-charged battery backup system installed in a health centre in The Gambia.](image)

**Figure 4.3:** Grid-charged battery backup system installed in a health centre in The Gambia. Charger and DC-to-AC inverter are mounted to the wall, with electrical connection from the inverter fed into the paediatric ward to outlets that are designated for concentrator use only. Battery rack with eight 6V, 350Ah VRLA maintenance-free batteries has a footprint of approximately 1.6m by 0.4m. (photo: B Bradley, 2011).

**Maintenance and cost**

Due to the complexity of the components (charger, inverter, and fused connections) some level of technical experience would be required to install the system and troubleshoot problems should they arise. Thus this system would only be viable in places where some technical resources are available. The display on the charger chosen for the prototype system in The Gambia was quite visually intuitive, with charge bars indicating the level of charge of the batteries, and the charging or discharging status. An inexperienced user could easily determine whether the system was operating as expected and could notify technical staff accordingly.

Although more costly, maintenance-free sealed batteries were chosen for the system in The Gambia specifically for ease of maintenance. Once installed, it was expected that this system would require little day-to-day maintenance beyond periodic dusting of the battery bank and other wall-mounted components. All major components (oxygen concentrator, batteries, inverter, and charger) have an expected lifespan of five years or greater under normal operation conditions [17]. The system in The Gambia required one replacement charger in the first five years of operation due to a catastrophic power
surge. Such events are difficult to predict and prevent, so contingencies such as surge protection can be put in place to mitigate this risk.

Cost for such a system will vary considerably depending on the required battery capacity, which is specified based on the availability of grid electricity per day. The estimated cost for the battery system in The Gambia was about US $8,900. The cost model presented in Bradley et al. (2012) [24] was used to calculate estimated system costs ranging from about US $5,000 to $8,900 for electricity availabilities ranging from 22 down to 4 hours per day, respectively (i.e., the more grid electricity that is available, the less battery capacity required, and the lower the cost). Table 4.4 provides a summary of the estimated costs used in the OxOpt model.

Table 4.2: Attributes and limitations of grid-charged battery backup oxygen delivery system\textsuperscript{a}.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>• All components readily available; one system has been implemented in The Gambia\textsuperscript{a,b,c}.</td>
<td>• Installation and maintenance technically more complex than UPS system.</td>
</tr>
<tr>
<td>• Can be integrated into a health facility ward such that health workers interface with concentrators and flowmeters only, by wiring sockets directly to the battery system in another room (as demonstrated in The Gambia\textsuperscript{c}).</td>
<td>• Charger and inverter components tend to be weakest link with shortest lifespans. They are vulnerable to extreme voltage surges. Built-in surge protection protects against fire risk; external surge protection equipment will add to the overall system cost.</td>
</tr>
<tr>
<td>• In the event of a power outage, no user intervention is required and there is no interruption in oxygen supply.</td>
<td>• If batteries, charger, and inverter are isolated in another room, problems may not be immediately apparent to users.</td>
</tr>
<tr>
<td>• Maintenance-free batteries can be used. Minimal maintenance required for other components.</td>
<td>• Electrical sockets designated for concentrator use only may be subject to misuse in the event of a power outage unless properly monitored.</td>
</tr>
<tr>
<td>• Maintenance-free batteries also emit less volatile fumes, which can be a safety concern with other battery types.</td>
<td>• The concentrator will run off the batteries at all times; may affect the life of both the batteries and inverter.</td>
</tr>
<tr>
<td>• Components expected to last at least 5 years.</td>
<td>• Battery life sensitive to high ambient temperature\textsuperscript{c}.</td>
</tr>
<tr>
<td>• When batteries are fully charged, and grid power is on, charger switches to ‘conservation charging’ mode such that batteries do not overcharge and produce fumes.</td>
<td>• Cost-effective for settings with good to poor power (at least four hours per day) and a wide range of health centre sizes (i.e., between 500 and 6000 admissions per year)\textsuperscript{d}.</td>
</tr>
<tr>
<td>• Consistency of voltage provided by the inverter will help prolong the life of concentrators.</td>
<td>• Batteries sensitive to high ambient temperature\textsuperscript{c}.</td>
</tr>
</tbody>
</table>

\textsuperscript{a} Adapted from Bradley et al. (2012) [23] © IEEE 2012; \textsuperscript{b} Bradley et al., (2011) [17]; \textsuperscript{c} Bradley et al., (2012) [22]; \textsuperscript{d} Bradley et al., (2012) [24]

4.3.3 Off-grid solar-powered system: Very poor or no electricity availability

System overview

A solar-powered system is appropriate for settings with very little to no grid electricity available. In this system, solar panels are used to charge batteries. The system consists of photovoltaic (PV) panels, a solar charge controller, a battery bank, and a DC-to-AC inverter (Fig. 4.4). Concentrators operate from the battery bank when the sun is not available for charging; otherwise solar panels power the concentrators directly as regulated by the charge controller. Ideally, concentrators would operate on an independent circuit connected to the solar system to avoid the need for user intervention regardless of the solar irradiation and level of charge of the system [23, 24].
To power a 350W concentrator, the cost and footprint of these systems is considerable. As with the previous systems, appropriately scaled components would have to be selected and installed to suit the specific application requirements. The main considerations in this case are location-specific average daily solar radiation values, the angle of the PV panels relative to solar radiation (if the panels do not track the sun), and the expected duration of periods without sun (e.g., consecutive cloudy days). Solar radiation is dependent on geography and affects the power storage necessary to compensate for when the batteries are not being charged. Solar panel efficiency drops significantly on cloudy or rainy days, or with dust build up. This is an important consideration as rainy season is often accompanied by increased prevalence of respiratory illnesses, leading to higher demand for oxygen [19]. System attributes and limitations are summarized in Table 4.3.

Evidence in the field

The first published case of using solar panels as an alternative power source for oxygen concentrators was from The Gambia in 2001 at a rural mission hospital [118]. At the time, the health facility had grid electricity for just 2-3 hours per day and already had an established solar system for other uses. Upgrading the existing solar system for an oxygen concentrator required adding 24 panels and six batteries. It was estimated that for 2-3 days at a time, 1-2 weeks a year during the rainy season months and during the dusty Hamartan season, the solar-powered system would be inadequate on its own, necessitating a backup oxygen supply. It is unknown whether the system is still operational.

More recently, a pilot project was conducted at a four-bed paediatric intensive care unit (ICU) in Uganda to demonstrate the feasibility of a solar-powered oxygen concentrator in a low-resource setting [133]. The system, consisting of 25 80W panels and eight 220Ah batteries, was successfully used to treat a study cohort of 28 paediatric patients presenting with respiratory illness and hypoxaemia over a 5-month period. The system experienced one major failure during the study period; the battery bank was completely depleted due to low solar energy input during a period of heavy rainfall and cloud cover.
They found the system efficiency to be less than ideal. Compared to the theoretical maximum daily energy output, the median PV array efficiency was only 50% (range 27 – 66%), with periods of visible cloud and/or rain associated with lower array efficiency (median 17%, range 0 – 43%) compared to sunny periods (median 55%, range 11 – 96%) [133].

Maintenance and cost

Due to the complexity of the solar system components, a high level of technical experience would be required for installation and troubleshooting. Thus this system would only be viable in places where some technical resources are available or accessible. Once installed, this system would require day-to-day maintenance including periodic dusting of the battery bank and other wall-mounted components, as well as frequent washing/dusting of the PV panels. As reported by Schneider [118], none of these tasks are labour intensive but they require commitment on the part of the staff and administration.

The initial capital investment required for solar technology may be prohibitively expensive in many cases, limiting its widespread use. The estimated capital costs for the Gambian and Ugandan field trials were about US $13,000 in 2001 [118] and US $18,000 in 2013 [133], respectively. Our cost model estimates that the capital cost of solar powered systems will always be higher than grid-charged battery systems, regardless of the status of grid electricity, due to the cost of solar panels [24]. However, the cost of solar panels has been dropping rapidly over the past decade; sources estimate price decreases between 68% to 76% since 2010 [123]. Operating costs are expected to be low; it was estimated that the recurrent costs for the solar system in The Gambia were US $51 per month [118].

All major components common to the battery backup system (oxygen concentrator, batteries, inverter, and charger) have an expected lifespan of five years or greater [17]. The lifespan of panels is estimated to exceed 25 years, however solar equipment warranties are subject to a company’s longevity in a rapidly changing industry [23]. For example, the industry has grown 51% annually since 2000, and it has been estimated that between 2008 and 2013 about 50% of over 200 venture capital-funded solar startups either went bankrupt, closed, or were acquired [141]. These realities should be taken into account when considering the lifespans and economics of this technology option.

4.3.4 Other options not included in the OxOpt model

Other alternative oxygen or energy sources that are not included as options in the OxOpt model are cylinders, oxygen storage systems and generators.

Cylinders

Several studies in low-resource settings [34, 76, 91, 105], including our recent assessment of oxygen concentrators at the MRC hospital in The Gambia [21], have demonstrated that oxygen concentrators are more cost-effective than cylinders, reporting cost savings of up to 75%. For this reason, cylinders are not explicitly considered as an oxygen source in the OxOpt model. Where viable, cylinders are a useful backup supply in the event that all other sources of oxygen fail.

Oxygen storage systems

Generating and storing oxygen when power is available is an alternative to storing energy in batteries, however experience with such systems in low-resource settings is limited. Oxygen storage systems were
Table 4.3: Attributes and limitations of off-grid solar-powered oxygen delivery system

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Similar attributes to the grid-charged battery system, plus;</td>
<td>• Most technically complex of all systems to install and maintain</td>
</tr>
<tr>
<td>• No grid power required; although the system could be configured to charge from grid power when available.</td>
<td>• Initial capital investment is relatively high (estimates range from US $10,000(^a) to US $18,000(^b).</td>
</tr>
<tr>
<td>• Panel life expectancy is quite long (&gt;25 years).</td>
<td>• If batteries, charger, and inverter are isolated in another room,</td>
</tr>
<tr>
<td>• Operating costs are relatively low(^c). The economic case will</td>
<td>problems may not be immediately apparent to users.</td>
</tr>
<tr>
<td>continue to improve as solar cell prices drop and electricity rates</td>
<td>• Battery life sensitive to high ambient temperature(^d).</td>
</tr>
<tr>
<td>rise.</td>
<td>• Dependent on hours per day of viable solar radiation (e.g., seasonal</td>
</tr>
<tr>
<td>• All components would be readily available; at least two systems</td>
<td>fluctuations due to rainy or Hamaratan (dusty) season) and may require</td>
</tr>
<tr>
<td>have been field tested(^e).</td>
<td>backup cylinders if not properly specified for these periods of low</td>
</tr>
<tr>
<td></td>
<td>sunlight.</td>
</tr>
<tr>
<td></td>
<td>• Panels require regular (daily) washing otherwise charging</td>
</tr>
<tr>
<td></td>
<td>efficiency is greatly reduced(^f).</td>
</tr>
<tr>
<td></td>
<td>• Solar panels installed outside the facility (i.e., roof or ground</td>
</tr>
<tr>
<td></td>
<td>mounted) may be subject to tampering.</td>
</tr>
</tbody>
</table>

\(^a\) Adapted from Bradley et al., (2012) [23]; \(^b\) Schneider (2001) [118]; \(^c\) Bradley et al., (2012) [24]; \(^d\) Hawkes et al., (2016) [133]; \(^e\) Bradley et al., (2012) [22]

explored early in this research, but were not considered further as they were deemed inferior and more costly compared to energy storage systems [23, 24]. For example, in terms of technical complexity, maintenance, and usability, the oxygen storage options were ranked lower than battery and solar-powered systems due to the changes that would be required for integration into a health facility setting such as additional training and personnel to manage and maintain the cylinder or reservoir refilling process [23].

We considered both commercial oxygen generation and storage systems as well as a ‘do-it-yourself’ oxygen storage concept, assembled using a conventional concentrator and a compressor to pressurize oxygen for storage in a reservoir. Commercial systems include the Airsep Ultrox (Buffalo, NY), the Invacare Homefill Ambulatory system (Cleveland, OH), and the Diamedica Oxygen Reservoir Filling System (Devon, UK). The Ultrox is a transportable unit designed to fill multiple oxygen cylinders simultaneously for high volume situations such as disaster relief or temporary medical or military facility installations. The Invacare Homefill Ambulatory system is designed for patient home use. The Diamedica Oxygen Reservoir Filling System is designed for healthcare settings in low-resource settings but can store just 100 to 500 litres of usable oxygen. The estimated costs of such systems range from about US $5,000 (for the Invacare and Diamedica systems) to US $20,000 (for the Ultrox) [23].

Generators

A 2013 survey of health facilities across sub-Saharan Africa found that a low proportion (10 – 29%) reported having functional generators with fuel available at the time of the assessment [1]. In our experience in The Gambia, many hospitals and health centres have backup generators, but they suffer from similar challenges as cylinders – e.g., cost and transport logistics (of fuel) – and are often only used in emergencies. This was also the experience of the solar-powered concentrator researchers in Uganda, who reported anecdotally that the generator was rarely started during power interruptions, due to lack of fuel or lack of access by ward staff to the locked generator [133]. As such, we did not consider generators to be a reliable source of backup power for concentrators.
4.4 Chapter 4 Design Implications for the OxOpt Model

Given the attributes, limitations, and previous cost modelling [24] of the systems presented above, a flow chart (Fig. 4.5) was developed to guide the choice of alternative energy option for concentrators. As will be shown later in Chapter 6, this flow chart is essential to the ‘options analysis’ phase of the Health Needs Assessment (HNA) process within which the OxOpt model would be used in a real-world application. This chart should be used in consultation with local stakeholders who have extensive knowledge about the situation and resources available at each health facility of interest [20,152].

The chart is used to preferentially suggest the alternative energy source that is most appropriate for each health facility, given the status of grid electricity, as well as the cost and feasibility of the different options. For example, the chart suggests that solar should only be considered in settings with less than four hours of grid supply per day. As was shown above with the battery system implemented in The Gambia, just 4 hours of electricity per day (which in many locations is less than the hours of viable solar radiation) is enough to charge batteries to produce continuous oxygen 24/7 [17]. In other words, if grid power can provide just as many charging hours as solar irradiation, the cost of PV panels can be avoided. Cylinders are considered a ‘last resort’ due to their cost and logistical challenges [21,34,76,91,105].

Estimated costs for various alternative energy systems, presented in Table 4.4, are based on experience from The Gambia [17,21,24,63] and elsewhere [118,133]. Based on the option chosen, and the amount of grid availability per day, the OxOpt model uses this lookup table when calculating alternative energy capital equipment costs for each health facility. In a real-world application as part of the HNA process, there would likely be a tender process initiated to solicit supplier proposals and quotes once the required alternative energy options are determined. This evaluation would occur whether the oxygen project is a government-initiated project or funded by a third party. The costs in Table 4.4 would thus need to be updated to reflect the specific context before running the model.

In summary, a decision about which alternative energy source is appropriate for each health facility being modelled, and an estimated capital cost for that system, are pre-requisite inputs to the OxOpt model. The goal of the model is not to propose component-level system designs (e.g., how many solar panels, of what wattage, etc.); the component database needed to do so would be obsolete as soon as it is developed, or irrelevant in many contexts where there are rules or processes in place for equipment procurement from approved suppliers, etc [152]. The goal, rather, is to evaluate whether the investment in the additional technology meets costs constraints, or is expected to sufficiently improve health outcomes to warrant the investment.
Figure 4.5: Flow diagram guiding choice of alternative energy source for powering oxygen concentrators in settings with poor grid power. Due to estimated increasing system costs, the chart preferentially selects the most cost-effective option given the amount of grid electricity available.

* Either due to scheduled grid blackout periods or random grid interruptions. Data should be collected as part of a situational analysis (see Chapter 6) to determine power interruption patterns. Such data has been collected for The Gambia (see section 8.2.3).
** Considerations include: daily solar irradiation, space for mounting panels, on-site technical capacity for maintenance and upkeep
*** Considerations include: workable transport, distance from oxygen plant
Table 4.4: Estimated costs of alternative energy options for oxygen concentrators.

<table>
<thead>
<tr>
<th>Option #</th>
<th>Alternative Energy Type</th>
<th>Hours electricity per day</th>
<th>Capital Cost ($USD)</th>
<th>Cost per 6000L ($USD)</th>
<th>Notes and source</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>None</td>
<td>24</td>
<td>$0</td>
<td></td>
<td>Only concentrators needed</td>
</tr>
<tr>
<td>1</td>
<td>Uninterrupted power supply (up to 5 concentrators)</td>
<td>22 to 24</td>
<td>$4,000</td>
<td>Bradley et al., (2016)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 to 22</td>
<td>$5,160</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>16 to 19</td>
<td>$5,260</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>12 to 15</td>
<td>$5,500</td>
<td></td>
<td>Bradley et al., (2012)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8 to 11</td>
<td>$7,296</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>7</td>
<td>$8,097</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>6</td>
<td>$8,401</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 to 5</td>
<td>$8,928</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Grid-charged battery backup</td>
<td>1 to 3</td>
<td>$8,967</td>
<td>Bradley et al., (2012) and data from contacts in The Gambia, unpublished</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0</td>
<td>$18,000</td>
<td></td>
<td>Hawkes et al., (2016)</td>
</tr>
<tr>
<td>5</td>
<td>Cylinders</td>
<td>0</td>
<td>$48.50</td>
<td></td>
<td>Howie et al., (2009)</td>
</tr>
</tbody>
</table>

All estimates are based on analyses for The Gambia context [21, 24, 63] except for the off-grid solar system, which is based on Hawkes et al. (2016) [133]. Cost for UPS is for up to 5 concentrators. Battery backup and solar system costs are on a per concentrator basis. Cylinder backup cost is per standard cylinder refill (i.e., 6000L) in The Gambia including transport.
Chapter 5

Demand Side: Using OR to Estimate Demand for Oxygen

This work has been previously published (full citation: Bradley, BD et al. Estimating oxygen needs for childhood pneumonia in developing country health systems: A new model for expecting the unexpected. PLoS ONE, 9(2):e89872, 2014 [19]). It has been reproduced here (sections 5.1 - 5.5) without changes under the Creative Commons Attribution (CC BY) license. Changes to the model post-publication and implications for the OxOpt model are described in section 5.6. Appendix B provides supplementary details on the random variables and distributions used in the model.

5.1 Abstract

Background: Planning for the reliable and cost-effective supply of a health service commodity such as medical oxygen requires an understanding of the dynamic need or ‘demand’ for the commodity over time. In developing country health systems, however, collecting longitudinal clinical data for forecasting purposes is very difficult. Furthermore, approaches to estimating demand for supplies based on annual averages can underestimate demand some of the time by missing temporal variability.

Methods: A discrete event simulation model was developed to estimate variable demand for a health service commodity using the important example of medical oxygen for childhood pneumonia. The model is based on five key factors affecting oxygen demand: annual pneumonia admission rate, hypoxaemia prevalence, degree of seasonality, treatment duration, and oxygen flow rate. These parameters were varied over a wide range of values to generate simulation results for different settings. Total oxygen volume, peak patient load, and hours spent above average-based demand estimates were computed for both low and high seasons.

Findings: Oxygen demand estimates based on annual average values of demand factors can often severely underestimate actual demand. For scenarios with high hypoxaemia prevalence and degree of seasonality, demand can exceed average levels up to 68% of the time. Even for typical scenarios, demand may exceed three times the average level for several hours per day. Peak patient load is sensitive to hypoxaemia prevalence, whereas time spent at such peak loads is strongly influenced by degree of
Conclusion: A theoretical study is presented whereby a simulation approach to estimating oxygen demand is used to better capture temporal variability compared to standard average-based approaches. This approach provides better grounds for health service planning, including decision-making around technologies for oxygen delivery. Beyond oxygen, this approach is widely applicable to other areas of resource and technology planning in developing country health systems.

5.2 Introduction

Pneumonia is the leading cause of child mortality globally, representing 18% of the 7 million deaths under-five in 2011 [149]. Pneumonia is most prevalent during the rainy season in tropical regions, and during the cooler, drier winter season elsewhere [28, 52, 62, 68, 94, 95, 119, 134, 138]. Pneumonia is associated with severe hypoxaemia (arterial blood oxygen saturation, \( \text{SpO}_2 \), below 90%), a potentially fatal complication that requires oxygen therapy [37, 79, 124].

Medical oxygen is an important example of a health commodity that is not widely or reliably available in many low-income settings due to financial constraints, poor infrastructure (e.g., roads, electricity), and inadequate capacity for supply management and equipment maintenance [8, 38, 61]. Access to oxygen has been found to be particularly inadequate in paediatric wards due to insufficient supply and competition for use by other services [53]. Anecdotally, oxygen is often rationed to only the sickest children during busy periods [39]. The World Health Organization (WHO) even offers suggestions on how to prioritize the use of limited oxygen supplies [147]. Given that oxygen has been shown to reduce mortality from pneumonia in children by as much as 35% [41] improved oxygen supply to this patient population has the potential to substantially reduce child deaths.

To plan for reliable and cost-effective supply, the paediatric oxygen needs of a health facility must be understood, but collecting longitudinal clinical data is difficult in developing countries. One approach to overcoming this challenge is to periodically assess the supply/demand mismatch over a short time period (e.g., 24-hours [46]), but this does not capture oxygen shortages throughout the year nor provide insight into how to effectively adjust the supply to meet changing needs. Another approach is to project oxygen demand using average estimates of key factors (e.g., annual admission rate, treatment duration, flow rate, etc.) [63, 86]. However, this approach will underestimate oxygen demand a large proportion of the time because it does not consider peaks arising from: (a) seasonal variations in respiratory disease burden and the corresponding disproportionate need for oxygen, and; (b) random variations in patient-specific factors that occur on shorter time scales.

Given the difficulties in collecting long-term demand data, and the shortcomings of using averages, the objective of this paper is to present a discrete event simulation (DES) model for estimating demand for a seasonal health commodity, using the example of oxygen for childhood pneumonia. DES is a well-accepted computer simulation technique in health services research, particularly in the assessment and design of health care delivery systems, and in forecasting demand for human and physical resources [15, 48, 64, 66]. However, the application of DES to study health service delivery challenges in low-income countries is still in its infancy. Only recently have models been developed to evaluate the cost-effectiveness of new technologies or interventions [13, 74, 108], or the impacts of policy changes affecting service delivery operations [31] or supply chain logistics [6, 7]. To our knowledge, forecasting temporal
demand for a health commodity used in a critical care in-patient environment is a novel application of DES for low-income health systems.

We hypothesize that DES will provide realistic time-varying oxygen demand estimates, and will allow for the first time the ability to quantify temporal variations in simultaneous demand, expressed as either patient load or oxygen flow rate, at a health facility level. Oxygen demand due to childhood pneumonia is dependent on seasonality, annual case load, hypoxaemia prevalence, and variations in individual patients' prescribed flow rates and treatment durations. These key demand factors underpin our model and are described further below.

5.2.1 Factors affecting oxygen demand

**Seasonality.** Pneumonia among children is seasonal [2,36,67,94,95,129,138]. In the pneumonia “high season”, which typically lasts 3 to 5 months, the average monthly case load can be 20 to 90% greater than that of the “low season”, depending on the degree of seasonality (i.e., the proportion of total annual cases accounted for in high season) [62,67,129,138,139]. This seasonal difference in case burden is primarily due to outbreaks of viral pathogens, such as respiratory syncytial virus, during hot, rainy months in tropical regions [28, 62, 68, 72, 119, 139], and outbreaks of influenza viruses during cooler, drier months in more temperate regions [52].

**Pneumonia case load.** Although global estimates of pneumonia incidence and mortality are available [14,115,142], empirical data on admission rates for individual health facilities in low-income countries are scarce. A few studies have reported average annual pneumonia admissions ranging from about 50 cases at small rural health centres to over 1000 cases at district or main referral hospitals [61,73,86].

**Hypoxaemia prevalence.** Hypoxaemia prevalence among childhood pneumonia cases varies widely between geographic regions and at different altitudes, as well as with pneumonia severity [37,67,79,124]. An estimated 13.3% (IQR 9.3% - 37.5%) of WHO-defined pneumonia cases globally are hypoxaemic [124]; in lower-lying African countries, prevalence ranges from 3 to 10%, whereas in Asia at higher altitudes prevalence ranges from 9% to 39%.

**Flow rate.** The WHO-recommended flow rates when using nasal prongs are 0.5 L/min for young infants and 1 to 2 L/min for preschool aged children, with a maximum of 4 L/min [147,150]. On average, flow rates of 0.6 to 1.0 L/min are required to achieve > 90% SpO₂, with high inter-patient variability [92,93,140]. In practice, patients will often receive equal flow rates from a source split equally among multiple patients [86].

**Treatment duration.** The duration of oxygen therapy typically ranges from 2 to 5 days [147]. A study from The Gambia found mean treatment duration for children to be 3.65 ± 2.92 days [140]. Constant treatment durations of 3 and 2.8 days per patient were used to estimate oxygen demand in The Gambia [63] and Papua New Guinea [86], respectively, without considering variability.
5.3 Methods

5.3.1 Re-interpreting demand factors for a DES model: Input parameters and assumptions

**Seasonality.** We model pneumonia seasonality with a single high season once per year. The proportion of annual pneumonia cases concentrated in high season – or ‘degree of seasonality’ – is a fixed percentage, $P$. The high season duration, $D$, is a fixed value in months.

**Pneumonia case load.** Pneumonia case load is modeled using random patient arrivals following a Poisson Process [4, 126, 143] with rate parameter, $\lambda$, which denotes the number of pneumonia arrivals per year. The average monthly admission rate in high season is $P\lambda/D$. To smooth the admission profile between seasons, we assume one-month ramp up and ramp down periods as part of the high season, with monthly admission rates adjusted appropriately to reflect this profile while maintaining the prescribed high season average. In low season, the monthly admission rate is $(1 - P)\lambda/(12 - D)$ and does not vary by month.

**Hypoxaemia prevalence.** Although a range of values have been reported for hypoxaemia prevalence among pneumonia cases, $H$, no data is available regarding seasonal variability. We therefore assume $H$ to be invariant across seasons. The number of hypoxaemic cases, however, will vary seasonally since pneumonia incidence is seasonal.

**Flow rate.** Prescribed flow rate, $F$, is modeled as a random variable based on a modified Poisson distribution with a mean, $\rho$, of 1 L/min, a minimum value of 0.5 L/min, and discrete allowable values in increments of 0.5 L/min. This distribution reflects the WHO recommendations for infants and children [147, 150] and the reality that most patients likely receive 0.5 L/min or 1 L/min due to flow-splitting technology limitations [86]. The same distribution is used for high and low seasons.

**Treatment duration.** An exponential distribution with a mean, $\mu$, of 3.5 days is used to describe the random treatment duration, $T$. An exponential distribution is a special case of the Weibull distribution, which is widely used to model ‘length of stay’ in health services [83, 116].

5.3.2 Model mechanics and output

The DES model was developed in Matlab (MathWorks Inc., Natick, MA). Events are simulated over a one-year period, beginning with the first day of low season. Each arriving patient generated by the Poisson Process is randomly assigned to a state of hypoxaemic (needs oxygen) with probability $H$; hypoxaemic patients are further randomly assigned a flow rate and a treatment duration according to the distributions described earlier (see Fig. 5.1). At the end of the 365-day simulation period, any remaining treatment time for patients in the system are wrapped around to the beginning of the simulation year.

Simulation mechanics are illustrated in Fig. 5.2. Random arrival times result in patients being present simultaneously for random periods of time. The number of simultaneous patients requiring oxygen and their collective flow rate vary in an uncorrelated fashion because oxygen requirements differ from patient to patient.

The simulation output is aggregated into an hour-by-hour account of patient load and collective flow rate. The output can be further analyzed to determine total demand, variability in demand, or
maximum peaks in demand, for any time scale (e.g., daily, monthly, seasonally, annually). These metrics are then analysed across the desired number of simulation iterations.

Figure 5.1: **Process flow diagram of a patient’s pathway through the simulation.** Simulation continues until 365 days are reached.
Figure 5.2: Example timeline view of simulated patient arrivals and variable assignments. Lower portion shows simulation ‘events’. Upper portion shows changing level of simultaneous patients on oxygen and collective flow rate (L/min) over time.

5.3.3 Scenario analysis

Three scenarios were selected to represent a wide range of health facilities. Input parameters for all scenarios are summarized in Table 5.1. 500 iterations were conducted for each set of conditions.

Scenario 1 illustrates the implications of considering demand on an hourly basis by visually comparing DES output for a typical setting with estimates from an average-based approach characterized by the same annual case load and hypoxaemia prevalence, but no seasonal variation, and constant (average) values for flow rate and treatment duration.

Using the same hypoxaemia prevalence ($H$), degree of seasonality ($P$), and high season duration ($D$) as Scenario 1, annual pneumonia case load ($\lambda$) was varied from 50 to 2,000 in Scenario 2. Total oxygen demand was computed for both high and low seasons and compared to average-based demand estimates.

For Scenario 3, $H$ and $P$ were varied to explore the effects of these context-specific factors on peak demand. Three levels of $H$ (10%, 20% and 30%) covering the interquartile range of the global systematic review [12], and three levels of $P$ (35%, 45% and 55%) were selected, giving nine combinations of these two parameters. Note that for a 4-month high season, $P= 35\%$ represents a very low degree of seasonality (i.e., 35% of cases in $33\frac{1}{3}\%$ of the year). We analyzed ‘peak demand’ in terms of both patients and time. First, we found the maximum simultaneous patient load in each season. Then, we computed the amount of time spent at or above selected peak patient load thresholds, as well as the amount of time that demand (collective flow rate) exceeded average-based estimates.
Table 5.1: Input parameters for modeled scenarios.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Parameter</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual pneumonia case load</td>
<td>$\lambda$ (patients/year)</td>
<td>500</td>
<td>50 to 2,000</td>
<td>500</td>
<td>[61,73,86]</td>
</tr>
<tr>
<td>Hypoxaemia prevalence</td>
<td>$H$ (%)</td>
<td>13</td>
<td>13</td>
<td>10, 20, 30</td>
<td>[124]</td>
</tr>
<tr>
<td>Seasonality</td>
<td>$P$ (%)</td>
<td>45</td>
<td>45</td>
<td>35, 45, 55</td>
<td>[62,67,129,138,139]</td>
</tr>
<tr>
<td></td>
<td>$D$ (months)</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>[2,36,67,129,138]</td>
</tr>
<tr>
<td>Flow rate</td>
<td>$F$ (L/min)$^a$</td>
<td>$\rho = 1$</td>
<td>$\rho = 1$</td>
<td>$\rho = 1$</td>
<td>[86,147,150]$^c$</td>
</tr>
<tr>
<td>Treatment Duration</td>
<td>$T$ (days)$^b$</td>
<td>$\mu = 3.5$</td>
<td>$\mu = 3.5$</td>
<td>$\mu = 3.5$</td>
<td>[63,140,147]$^c$</td>
</tr>
</tbody>
</table>

$^a$ Random variable with modified Poisson distribution; $^b$ Random variable with exponential distribution; $^c$ References support parameter value selection, not the type of distribution chosen to describe the demand factor.

5.4 Results

5.4.1 Model verification

All input parameters for Scenario 1 fell within the 95% confidence intervals of the corresponding simulated outcomes (Table 5.2).

Table 5.2: Verification of model output for Scenario 1.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Parameter</th>
<th>Scenario 1 Input</th>
<th>Simulation (Mean [95% CI])</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual pneumonia case load</td>
<td>$\lambda$ (patients/year)</td>
<td>500</td>
<td>500.5 [498.5, 502.5]</td>
</tr>
<tr>
<td>Hypoxaemia prevalence</td>
<td>$H$ (%)</td>
<td>13</td>
<td>13.1 [12.9, 13.2]</td>
</tr>
<tr>
<td>Seasonality</td>
<td>$P$ (%)</td>
<td>45</td>
<td>44.8 [44.6, 45.0]</td>
</tr>
<tr>
<td></td>
<td>$D$ (months)</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Flow rate</td>
<td>$F$ (L/min)$^a$</td>
<td>$\rho = 1$</td>
<td>1.00 [0.99, 1.00]</td>
</tr>
<tr>
<td>Treatment Duration</td>
<td>$T$ (days)$^b$</td>
<td>$\mu = 3.5$</td>
<td>3.51 [3.47, 3.54]</td>
</tr>
</tbody>
</table>

5.4.2 Scenario results

Scenario 1: Figure 5.3 illustrates how hourly oxygen demand fluctuates throughout the year due to seasonality and variability in patient arrivals, treatment duration, and flow rate. Only five out of the 500 iterations (i.e., simulated years) of Scenario 1 are shown. Constant flow rate demand corresponding to an average-based estimate, as well as double (2X) and triple (3X) this average estimate, are also shown. Simulated demand exceeds the constant average-based estimate 29.3% and 43.8% of the time in low and high season, respectively. Demand often exceeds the 3X level for several consecutive days, even in low season (Fig. 5.3).

Scenario 2: In Scenario 2, oxygen demand increases with increasing annual pneumonia case load ($\lambda$), as expected (Fig. 5.4). When aggregated as annual totals, simulated estimates match closely with average-based estimates. However, the DES approach allows for the calculation of seasonal totals as well as year-to-year variability from multiple iterations. For example, the standard deviation of annual
Figure 5.3: **Hourly oxygen demand for a typical health facility.** Scenario inputs were 500 pneumonia admissions per year \((\lambda)\), degree of seasonality \((P)\) of 45%, high season duration \((D)\) of 4 months, and hypoxaemia prevalence \((H)\) of 13%. Different coloured lines represent five distinct simulation iterations. Horizontal lines represent the average-based estimate (solid), as well as 2 and 3 times this estimate (dashed), for this particular scenario. Prolonged periods of 4.4 and 7.8 days exceeding 3 times the average level in low season are shown.

High-season oxygen demand across iterations ranges from about 15% of the mean high season volume for \(\lambda = 2,000\) to over 90% for \(\lambda = 50\), suggesting that smaller health centres have much less predictable oxygen needs from year to year (Fig. 5.4). Trends were identical for low season (figure omitted).

**Scenario 3:** Results from Scenario 3 on the effects of hypoxaemia prevalence and degree of seasonality are shown in Figs. 5.5 and 5.6. Figure 5.5A shows a sensitivity matrix of maximum simultaneous patient load expected in high season. Maximum patient load nearly doubles as \(H\) increases from 10% to 30%, as shown by the sharp gradient from bottom to top. Maximum patient load also increases with \(P\), but with a weaker dependence than \(H\). Similar observations were seen for low season (figure omitted).

The duration of time that patient load is at or above selected thresholds – representing possible health facility capacity limits – is also an important consideration. \(P\) strongly influences the time spent at or above peak patient load thresholds during high season, as shown by the sharp gradient from left to right in Fig. 5.5B. For example, the amount of time at or above five patients is five times greater where \(P = 55\%\), compared to where \(P = 35\%\) (i.e., very little seasonality). Conversely in low season, the amount of time above peak patient thresholds is greater when \(P\) is lower.

Figure 5.6 shows peak demand in terms of the amount of time that simulated demand exceeded average-based estimates, and double and triple these estimates. With increasing \(H\) and \(P\), oxygen demand exceeded average-based estimates anywhere from 9.5 to 16.4 hours per day in high season. In low season, demand exceeded the average between 6.7 and 11.4 hours per day (low season results not shown in figure).

As \(H\) increases, the 2X and 3X estimates increasingly encompass true variability in demand, as shown by the darkening gradient from top to bottom in Fig. 5.6B and C. For example, at \(H = 10\%\), demand exceeds the 3X estimate by as much as 3.6 to 6.2 hours per day in low and high season, respectively; while the corresponding values when \(H = 30\%\) are only 0.9 and 3.7 hours, respectively (low season results not shown in figure). We hypothesize that with lower \(H\), the flow rate and treatment duration are more
dominant sources of variability, causing demand to fluctuate widely around lower constant average-based demand estimates.

Figure 5.4: **Total oxygen demand and year-to-year variability in high season for pneumonia admissions** ($\lambda$) **ranging from 50 to 2000.** Other scenario inputs: degree of seasonality ($P$) of 45%, high season duration ($D$) of 4 months, and hypoxaemia prevalence ($H$) of 13%. Mean high season volume is averaged across 500 simulation iterations (right axis). Standard deviation as a percentage of the mean high season volume is plotted to represent variability across simulation iterations (left axis).

Figure 5.5: **Peak demand in high season, measured in terms of both patients and time.** Sensitivity matrices show (A) maximum simultaneous patient load in high season; and (B) amount of time (hours) patient load exceeds selected peak patient load thresholds in high season, for hypoxaemia prevalence ($H$) ranging from 10 to 30% and degree of seasonality ($P$) ranging from 35 to 55%, averaged across 500 simulation iterations. In (B) thresholds of 3, 4 and 5 simultaneous patients were used for $H$ levels of 10%, 20%, and 30%, respectively. Results are for $\lambda = 500$ pneumonia admissions per year.
5.5 Discussion

We present a model for estimating oxygen demand due to childhood pneumonia, which leverages the distinctive time-based approach of DES in order to capture temporal variability in key demand factors. Modeling results for a range of hypothetical low-resource settings reveal that substantial year-to-year variability in oxygen demand can exist, particularly for small health facilities. We also show that average-based estimates can severely underestimate demand during seasonal highs as well as random peaks throughout the year; for as many as 16 hours per day in high season, and as many as 11 hours per day in low season. This means that with a system tailored to meet average demand levels, oxygen shortages may be experienced up to 68% of the time in high season, and about half the time in low season, leaving many patients under-served or even untreated altogether.

Our approach also enables the analysis of sensitivity to different demand factors; such inter-dependent relationships can help inform oxygen supply planning. For example, maximum patient load was more dependent on hypoxaemia prevalence, whereas time at or above peak demand loads was more dependent on degree of seasonality. Maximum patient load has implications for the physical technology capacity needed to meet demand (e.g., number of oxygen concentrators, flow-splitting devices, nasal prongs, etc.), whereas time spent at certain demand levels has implications for more temporally-based supply management and planning issues, both financial and logistical (e.g., cost per kWh to operate concentrators and/or generators, cylinder depletion rates and refilling frequency, etc.). Thus, to accommodate peak patient loads, it might be more important to plan around hypoxaemia prevalence, whereas to accommodate sustained time at peak loads, the degree of seasonality would be the foremost factor to consider. Our approach also allows for the analysis of how such interdependent relationships might differ between low and high season, which could inform better temporally-based oxygen supply planning.

For health technology decision-makers, the issue of oxygen supply is wrought with trade-offs. Systems that meet wide-ranging demand requirements will have positive health benefits but may have high operating costs and oxygen surplus during low demand periods, whereas systems meeting average demand criteria may adequately account for periods of high variability in demand resulting in adverse health
consequences. Our model could thus help determine what strategic mix of both a ‘fixed’ technology system (e.g., concentrators with adequate power supply) meeting some baseline demand, and a contingency backup supply (e.g., additional concentrators, cylinders, or other means of oxygen storage), may be required to cost-effectively meet variability in demand in both low and high seasons. For example, our model could inform decisions about how many concentrators to purchase to meet the majority of expected demand and how much stored oxygen to stock to meet short-term variability beyond the capacity of the concentrators. Model estimates of maximum patient load during high season could inform decisions about the layout of a ward to ensure that adequate access points to oxygen are available to accommodate all patients during busy periods. With estimates of how demand is distributed between low and high seasons, our model could also help inform how to appropriately split budgetary resources between low and high seasons to ensure adequate financial resources are reserved for increased electricity usage, or cylinder refilling, during peak periods.

Our simulation model can be further developed in several areas, particularly with the availability of better data. First, hypoxaemia prevalence has been found to be age-dependent, with higher occurrences in neonates compared to older children [67]. Including age variation will be important where age-dependent demand has implications for oxygen technology planning (e.g., different ward locations for neonates, infants and children). Second, hypoxaemia prevalence among pneumonia admissions may be higher during high season, due to increasing severity of illness [67]. The flow rate distribution may also shift to higher levels, corresponding to more severe illness in high season. We lacked sufficient data to model such variations. Third, hypoxaemia is also prevalent in non-pneumonia conditions. For example, high hypoxaemia rates have been found in children with malaria, meningitis, and malnutrition [124]. As more becomes known about hypoxaemia prevalence, our model can easily integrate the compounding effects of multiple illnesses on oxygen demand by simulating separate illness-specific admission streams, each with their own unique admission rate, degree of seasonality, and treatment considerations. By focusing on childhood pneumonia, we are taking a major step towards addressing total paediatric oxygen demand, as it is more likely that pneumonia cases are screened for hypoxaemia and prescribed oxygen. An integrated approach to identifying and treating hypoxaemia in other common childhood illnesses is an issue that deserves serious attention, especially if the oxygen needs of such illnesses are to be adequately met [124]. Lastly, the model could be applied beyond paediatric applications incorporating estimates of oxygen needs for other clinical services (e.g., surgery, adult respiratory illnesses) if data on the five key factors affecting demand represented in the model are available.

The DES model presented demonstrates a novel approach to estimating oxygen demand due to childhood pneumonia in low-resource settings. The model provides a more realistic estimate of time-varying demand at the health facility level, and can be applied to a wide range of geographies by choosing appropriate context-specific inputs. Oxygen is a unique health commodity in that managing the supply can be decentralized to the facility level with the use of local oxygen generating technology. Thus, a better understanding of oxygen need dynamics at the facility level could go a long way in improving health systems planning and cost-effective decision-making around oxygen technologies.

Despite the widespread use of DES in health services research, its application to low-income settings is relatively new. DES can be applied to any health commodity with a temporal demand profile (e.g., rapid malaria diagnostic tests, seasonal vaccines or drug treatments); thus the potential impact of DES as a technique for health resources forecasting is significantly broader than the problem of oxygen.
5.6 Chapter 5 Design Implications for the OxOpt Model

The DES model presented in this chapter is an integral part of the penultimate OxOpt simulation-optimization decision model for oxygen technology planning described in Chapter 7. After the model was published, the next phase of this work involved re-implementing the model in the Matlab SimEvents simulation environment and adding new features necessary for integration into the OxOpt model. This enhanced version will henceforth be called the Patient Arrival and O\textsubscript{2} Demand (PAOD) model (see section 7.2.1). The core design principles governing patient arrival dynamics and the tracking of simultaneous oxygen demand remain the same between the original publication and the new PAOD.

Enhancements made to the PAOD model before incorporation into the OxOpt model are as follows:

- Patient arrivals are still random according to a Poisson process, but health facility hours of operation for patient triage and intake are now restricted to better reflect reality. It is assumed that all health facilities can admit patients from 7am to 10pm (unique hours of operation could be tailored for each health facility if necessary). Patients that arrive outside of these operating hours are placed in a queue and are seen on a first-come-first-served basis when the health facility opens. The triage process is set to take 15 minutes per patient. As with the previous model, those patients requiring oxygen are randomly assigned a treatment duration and flow rate according to the probability distributions described in section 5.3.1 and Appendix B.

- Previously, the mean patient inter-arrival rate during the ramp-up and ramp-down periods surrounding the high season was decreased and increased, respectively, using a stepped approach. In the PAOD model, mean inter-arrival rates are fed into the model as a pre-determined time series signal that changes appropriately during the ramp-up and ramp-down periods, resulting in a smooth transition between seasons. Verification tests confirmed that the model was performing as desired; for several test scenarios, input parameters for patient admissions, both annually and within the low and high seasons, fell within the 95% confidence intervals for simulation runs of 500 iterations each.

- As will be shown in Chapter 7, the PAOD model interacts with other health facility sub-systems that track oxygen and electricity availability such that each patient can now be assigned a status of treated, partially treated, or untreated when they are discharged based on oxygen availability during their treatment period. This status is used to estimate the number of lives saved and other cost-benefit measures (see section 7.2.1).
Chapter 6

Overview of the *OxOpt* Model within a Health Needs Assessment Framework

6.1 Introduction

This chapter puts into context how the *OxOpt* model would be used in a real-world application. The model has two main objectives: (1) to act as a decision-support tool to determine the appropriate allocation of oxygen technologies across several health facilities to meet the needs of a specific context; and (2) to act as a theoretical advocacy tool to demonstrate the cost-effectiveness of oxygen therapy for a wide range of different scenarios and contexts, showing the tradeoff between cost and health outcomes. In either case, it is important to situate the use of this type of tool within a broader health needs assessment (HNA) framework [148,157,158].

Specifically for oxygen systems, the WHO highlights the importance of a HNA approach in their Technical Specifications for Oxygen Concentrators, stating “oxygen systems will be optimally effective if they are planned as part of an overall approach to improve quality of care within a hospital and a ward. A team approach is necessary, involving clinical staff, hospital administrators, engineers, and trainers” [152].

6.2 Situating the *OxOpt* Model within a Health Needs Assessment Framework

A health needs assessment is a systematic and evidence-based approach to identifying unmet health and healthcare needs of a population, and the commissioning and planning of health services to meet these unmet needs [157,158]. This process is particularly important in developing countries where the resources available for health care are limited, access to health care is usually both inadequate and inequitable, and there is a large variation in availability and use of health care by geographical area [158]. Stimuli for a health needs assessment can include the importance of a health issue for a particular population, evidence of the effectiveness of an intervention, or publication of new research findings about the burden
A health needs assessment provides the opportunity for:

- describing patterns of disease in a local population (e.g., hospital inpatient records to obtain numbers and causes of admissions) [157];
- highlighting areas of unmet need and providing a clear set of objectives to work towards meeting these needs;
- deciding rationally how to allocate resources in the most effective and efficient way;
- influencing policy, interagency collaboration, and/or research and development priorities [158]

Conducting a HNA involves both an epidemiological and a qualitative approach to determining needs and priorities that must balance clinical, ethical, and economic considerations – that is, “what should be done, what can be done, and what can be afforded” [158]. These three key questions are operationalized below as the following steps: (1) Situational analysis; (2) Options analysis; and (3) Optimization of options. The final step of implementation is considered beyond the scope of this thesis.

**Step 1: Situational analysis - what should be done?**

A situational analysis is the process of collecting relevant information for the setting of interest, and may involve a combination of qualitative and quantitative research methods [158]. A situational analysis aims to answer questions such as: What is the problem? What is the size and nature of the problem? What services are currently available? What do patients need? etc [158].

When using the *OxOpt* model, this contextual information becomes important country- and health facility-specific model inputs. For example, number of annual child pneumonia admissions, prevalence of hypoxaemia, duration of the peak season, electricity availability and power outage patterns, availability of local technician(s), etc. are all context-specific factors that are provided as input to the model.

**Step 2: Options analysis - what can be done?**

The options analysis aims to answer questions such as: What are the most appropriate and effective solutions, both clinically and in terms of cost? What are the resource implications? What are the outcomes to evaluate change and the criteria to audit success? etc [158].

In the case of the *OxOpt* model and decisions about alternative energy sources, the options analysis involves a feasibility assessment of the most appropriate technology options for each health facility. The analysis of Chapter 4, and the flow diagram in Fig. 4.5 in particular, provide guidance on the assessment of what is appropriate in each setting, given the availability of electricity, capacity for maintenance, etc. In practice, this process should take place in collaboration with local health administrators, engineers, equipment suppliers and funders [152]. In particular, the economics of these systems, including sizing, costing, and payment options would typically be discussed with manufacturers and local suppliers [152]. Depending on the setting, there may standard practices for tendering requests for such systems from suppliers and for evaluating these proposals.

This options analysis to determine which alternative energy source is most appropriate for each health facility, and the estimated capital costs for these systems, are pre-requisite inputs to the *OxOpt* model.
Step 3: Options optimization - what can be afforded? The OxOpt Model

This step involves a critical appraisal of the cost-effectiveness of the options considered in Step 2. In the context of the oxygen supply and demand problem, this is the HNA step where the OxOpt model can provide essential insight for resource allocation. Running the OxOpt model will provide recommendations for the number of concentrators needed at each facility, and whether alternative energy sources should be invested in, in order to meet oxygen demand and optimize cost-effective health outcomes.

Step 4: Implementation

The final and hardest step of a health needs assessment is translating the recommendations into policies and practices that will create beneficial change [157]. As described in Chapter 2, implementation can be facilitated if policy- and decision-makers are active in the process.

Although implementation of solutions recommended by the OxOpt model for The Gambia is outside the scope of this thesis, the model was designed specifically to fit within the remit of the HNA framework, such that its applicability in a real-world setting is a realistic possibility.
Chapter 7

Putting Supply and Demand Together: Technical Description of the \textit{OxOpt} Model

7.1 Overview of the \textit{OxOpt} Model

The \textit{OxOpt} simulation-optimization (SIM-OPT) model architecture consists of a discrete-event simulation model embedded within an optimization model. Figure 7.1 shows a conceptual diagram of the model architecture. The discrete-event simulation method was chosen in order to capture realistic aspects of health systems operations, such as patient management and resource demands, uncertainties in the availability of infrastructure and technology, and the interconnections and interdependencies among these components that affect patient outcomes. Simulation offers great flexibility and potential when a realistic characterization of a complex system cannot be put in an explicit analytical form \cite{85}. The optimization component, solved by way of a genetic algorithm, offers an efficient method to search for and identify optimal solutions with respect to relevant system performance measures \cite{85}. In a decision-support context, the solution to the optimization is a recommended course of action.

The simulation (SIM) model is implemented in Matlab’s \textit{SimEvents} environment. The optimization (OPT) model is coded using Matlab’s Optimization Toolbox. All model input parameters are entered into an Excel user interface and imported into Matlab.

The SIM model has two main purposes and is implemented as two sub-systems (Fig. 7.1):

\textbf{Sub-system 1: Health Facility Systems Model (HFSM)} - simulates patient arrivals and departures over time for all health facilities being modelled and tracks hourly demand for oxygen due to concurrent patient needs. Also simulates electricity supply and interruptions for all health facilities.

\textbf{Sub-system 2: Technology Systems Model (TSM)} - simulates oxygen technology solutions at each health facility and monitors how well the solutions meet oxygen demand by tracking oxygen availability throughout the simulation.
Figure 7.1: Conceptual block diagram of the OxOpt model and its major components; a discrete-event systems simulation (SIM) model and an optimization (OPT) model. HFSM = Health Facility Systems Model; TSM = Technology Systems Model; HF$_i$ represents a Health Facility Module; C represents a Concentrator Module; A represents an alternative energy source.

The HFSM consists of a grouping of $n$ Health Facility (HF) Modules (labeled HF$_i$ in Fig. 7.1), which are replicable Matlab library blocks with customizable health facility-specific parameters. Each HF Module consists of a Patient Arrival and O$_2$ Demand model (see Chapter 5), an Electricity Availability model, and a Monitoring and Data Storage system for monitoring the facility’s oxygen demand levels and the treatment status for each patient during their stay at the facility. Once initialized, the inputs to the HFSM sub-system remain unchanged for the remainder of model processing. A detailed description of the HF Module is provided in section 7.2.
Chapter 7. Putting Supply and Demand Together: Technical Description of the OxOpt Model

The HFSM sub-system is combined with a Technology Systems Model (TSM), which simulates implemented oxygen technology solutions across all health facilities in the HFSM network. Oxygen availability will depend on the quantity of oxygen concentrators recommended for each health facility (depicted as multiple Concentrator Modules, “C” in Fig. 7.1) and whether an alternative energy source is provided (depicted with “+A” in Fig. 7.1). When an alternative energy source is provided, continuity of electricity supply is maintained during all grid interruptions. Oxygen availability is also subject to grid power availability (governed by the HFSM sub-system) as well as equipment downtime due to repairs, which occur at random throughout the simulation according to patterns observed from the study of concentrator maintenance in Chapter 3 [18]. Like the HF Module, the Concentrator Module is a replicable custom Matlab library block, and is described in more detail in section 7.2. The TSM changes dynamically throughout the remainder of model processing, as the OPT model iteratively tests out different technology solutions in order to find the optimal setup.

Over the desired simulation time horizon, \(y\) (years), the HFSM and TSM of the SIM model work alongside one another to track satisfied and unsatisfied oxygen demand, as well as the capital and ongoing operating costs of the implemented system, which includes costs for electricity and maintenance. In a Monte-Carlo-like fashion, this process iterates for the desired number of iterations, \(j\), and summary metrics are averaged across all iterations and fed into the OPT model. The goal of the OPT model is to find the optimal allocation of oxygen technologies across all health facilities being modeled. This goal can be achieved through two different objective functions. The first and primary objective (Objective 1) is to minimize the total cost of the oxygen technologies required to satisfy some user-defined minimum threshold of total oxygen demand across all health facilities. For example, if a client health department wants to set a target that 80% of all oxygen need is to be satisfied, the model will suggest the technology setup that meets this goal for the lowest cost.

The second alternative objective (Objective 2) is to minimize unmet oxygen demand while staying within a fixed budget. For example, if the model is being run for a health ministry and the budget is known, the model will recommend a technology solution that maximizes satisfied demand while remaining under-budget. The mathematical formulations for these objective functions are provided in section 7.4.

The OPT model decision variables (regardless of which objective is chosen) are: (a) the quantity of oxygen concentrators needed at each health facility (integer decision variables, \(C_i\)), and (b) a decision about whether or not to invest in an alternative energy source at each facility (binary decision variables, \(A_i\), where 1 = yes and 0 = no).\(^2\)

The OPT problem is solved using a genetic algorithm (described in more detail in section 7.6). In an iterative manner the genetic algorithm chooses a set - i.e. a generation - of technology solutions to test. Each of these solutions are then ‘implemented’ in the TSM, and the SIM model will run with each technology solution in place over the desired time horizon for the desired number of simulation iterations. As mentioned above, at the end of this Monte Carlo-like simulation, key values (e.g., unmet oxygen demand, and costs of technology, electricity, and maintenance) are passed back to the OPT model in order to compute the ‘fitness’ of each solution - i.e., the value of the objective function. The genetic algorithm will intelligently chose another generation of solutions to implement, the simulation will run for each of these solutions, the objective functions are evaluated, etc. until the optimization

\(^1\)Typically the expected equipment lifespan, for ease of interpretation of total cost estimates.

\(^2\)Note that the specific choice of alternative energy technology has already been decided for each health facility during Step 2 of the Health Needs Assessment process presented in Chapter 6. The decision here is whether this investment should be made given budgetary constraints or constraints on allowable unmet demand.
converges to a generation containing the solution with the lowest cost (Obj 1) or lowest unmet demand (Obj 2) that meets all other constraints.

The OxOpt model has several outputs (Fig. 7.1). The OPT model provides the optimal technology solution (i.e., the values for all decision variables). The SIM model provides a complete breakdown of the estimated costs of the proposed solution (capital and operating), the amount of satisfied vs unsatisfied oxygen demand, technical outputs such as the number of repairs completed and kWh consumed, and the number of patients treated, partially treated and untreated, which are used to estimate the number of lives saved with oxygen. From these estimates, cost-benefit metrics such as cost per child treated, cost per life saved, and cost per disability-adjusted life-year (DALY) averted are also computed.

7.2 SIM Model Details

The SIM model was developed in Matlab SimEvents, a visual development environment specifically tailored to the simulation of event-driven systems. SimEvents models can easily be integrated with other Matlab functionality, including optimization.

7.2.1 The Health Facility Module of the HFSM

As shown in Fig. 7.2, each HF Module within the HFSM consists of a Patient Arrival and O2 Demand model (PAOD), an Electricity Availability model, and a Monitoring and Data Storage system for monitoring the oxygen demand levels of health facilities.

The Patient Arrival and O2 Demand model

The PAOD model of the HF Module was fully described in Chapter 5 with supplemental details on the model’s random variables in Appendix B. To summarize, patients “arrive” at the health facility at random according to a Poisson process. The annual patient admission rate is the user-defined parameter $\lambda_i$, but the model allows for seasonal variation in how these admissions are distributed. The proportion of admissions concentrated in the high season is designated by $\eta_i$.

In a Poisson process, the time between arrivals is described by an exponential distribution. For the PAOD, the mean of this exponential distribution is fed into the model as a time series signal that varies appropriately throughout the year (i.e., constant for low season, but changes in a linear step-wise fashion during ramp-up and ramp-down periods of $z_i$ days surrounding a high season – designated by the first, $\tau_{F_i}$, and last, $\tau_{L_i}$, month of the high season) to simulate a smooth increase and subsequent decrease in patient arrivals corresponding to the seasons. Once a patient arrives, they are “triaged” - i.e., designated a status of ‘hypoxaemic’ with probability $h_i$. Hypoxaemic patients are assigned a treatment duration, $T_i$, and a flow rate, $F_i$, both random variables.

All of these factors are user-defined input parameters, except for the treatment duration and flow rate distributions, which are fixed based on data and probability distributions from published literature (see Appendix B for more details).

Electricity Availability model

In addition to patient arrival dynamics, the HF Module also simulates the grid electricity supply at each health facility. There are two electricity situations considered by the model.
Chapter 7. Putting Supply and Demand Together: Technical Description of the OxOpt Model

Figure 7.2: The Health Facility Module implemented in Matlab SimEvents as a custom library block. An exploded screen capture of the internal block design, consisting of a Patient Arrival and O$_2$ Demand model (PAOD), an Electricity Availability model, and a Monitoring and Data Storage system, is shown.

- **Scheduled grid blackouts** ($\Phi_i$): Some health facilities may be subject to blackout periods as an energy rationing tactic by the national grid-supplied power system. The power outages are regular and tend to be for long durations. For example, for several health centres in The Gambia, power is off for 5 to 7 hours every 12 hours [17]. Input parameters for this scenario indicate the number of hours between blackouts, $\phi F_i$, (i.e., every 12 or 24 hours) and the duration of blackouts, $\phi D_i$, in hours. It is assumed that these blackouts are predictable.

- **Random grid interruptions** ($\Psi_i$): For health facilities that should have power 24 hours a day (either 24-7 grid supply or supplemented with a generator), random unexpected power outages can still occur. The frequency and duration of these interruptions are modelled as random variables that are normally distributed. Input parameters in this case indicate the mean time between interruptions ($\psi F_i$) and the mean duration of interruptions ($\psi D_i$), in hours. See Appendix B for more details.
Monitoring and Data Storage system

As patients are admitted and discharged throughout the simulation, the HF Module tracks simultaneous oxygen demand and, through interactions with the TSM, also tracks oxygen availability. Each patient that requires oxygen is assigned a status of fully treated, partially treated or untreated upon their departure from the facility. *Fully treated* means sufficient oxygen was available at the time of a patient’s admission and at the time of their departure. *Partially treated* means oxygen was available at admission but not at departure (or available at departure but not at admission) or the volume of oxygen available at their arrival and departure was insufficient to cover their full prescribed flow rate. *Not treated* means oxygen was not available at either admission or departure. Treatment status is relevant for the cost-benefit analysis conducted at the conclusion of *OxOpt* model processing (see section 7.5 for more details).

7.2.2 The Concentrator Module of the TSM

The availability of oxygen from concentrators is affected by device failures and the time required to complete repairs. The Concentrator Module (Fig. 7.3) models concentrator breakdowns and repairs according to two random variables; time between failures and duration of repairs (i.e. downtime due to repair). Data from Chapter 3 were used to determine probability distributions for these random variables; time between machine failures (hours) is $\sim \text{lognormal}(9.4, 0.8)$ and the duration of repairs (hours) is $\sim \text{exp}(1810)$ (see Appendix B for more details). In the TSM, when a concentrator is out of service it is unavailable to treat patients.

The combined oxygen output of all functioning concentrators at each facility is fed back to the HFSM, enabling patient treatment up to the volume available only if electricity is also available, either from grid supply (see Electricity Availability model, section 7.2.1) or from an alternative energy source installed at that facility, which provides continuity of electricity supply during grid interruptions (see section 7.2.3).

7.2.3 The choice of alternative energy technology for the TSM

As described in Chapter 6, an options analysis for each health facility would be performed before running the *OxOpt* model to determine the most appropriate alternative energy option. The flow diagram in Fig. 4.5 is designed to default to the best and most cost-effective option based on electricity availability and other more subjective assessment criteria (see Chapter 4 for a detailed analysis of alternative energy options). For each HF where the model recommends that the chosen alternative energy option be implemented (as depicted by “+A” in Figs. 7.1 and 7.3), this is communicated back to the Electricity Availability model of each HF module to ensure continuity of electricity throughout the simulation.

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2 An experiment consisting of a sample of 90 simulated patients was conducted to compare this classification method (based on just two discrete time points - at entry and upon departure) to patient statuses as determined through manual examination of simulation output. The two-point algorithm correctly classified patients 74% of the time, and patient outcomes (i.e., survivals, deaths) were not significantly different between the two-point approach and actual simulation output ($p=0.98$); that is, the two-point method correctly predicted the number of deaths to within 1.1%. There are no data in the literature that describe how patient outcomes may differ based on magnitude of ‘partial’ treatment and so magnitude of partial treatment is not tracked in the model (i.e., a patient receiving 25% of its total treatment time is considered to have the same mortality risk as a patient receiving 50% of its total treatment).
Figure 7.3: The Concentrator Module implemented in Matlab SimEvents as a custom library block. An exploded screen capture of the internal block design is shown.
7.3 OxOpt Model Parameters and Definitions

The nomenclature for all OxOpt model parameters is listed below:

**OxOpt Model Setup Parameters:**
- \( n \) number of health facilities (HF)
- \( y \) time period to be simulated (years), i.e., equipment lifespan
- \( j \) number of simulation iterations for embedded Monte Carlo SIM model

**SIM Model Parameters:**
- \( \lambda_i \) annual admission rate for HF \( i \), for \( i = 1, \ldots, n \)
- \( \tau F_i \) first month of high season for HF \( i \), \( \in [1, \ldots, \tau L_i - 1] \) for \( i = 1, \ldots, n \)
- \( \tau L_i \) last month of high season for HF \( i \), \( \in [\tau F_i + 1, \ldots, 12] \) for \( i = 1, \ldots, n \)
- \( z_i \) high season ramp up and ramp down duration (days)
- \( \eta_i \) proportion of annual admissions at HF \( i \) that occur in high season, for \( i = 1, \ldots, n \)
- \( h_i \) hypoxaemia prevalence among patient admissions at HF \( i \), for \( i = 1, \ldots, n \)
- \( \Phi_i \) binary parameter that is 1 if HF \( i \) is not subject to scheduled grid blackout periods and 0 otherwise, for \( i = 1, \ldots, n \)
- \( \Psi_i \) binary parameter that is 1 if HF \( i \) is not subject to random grid blackout periods and 0 otherwise, for \( i = 1, \ldots, n \)
- \( \phi F_i \) frequency (hours) of scheduled blackouts when \( \Phi_i = 0 \), for HF \( i \), \( \in [12, 24] \) hours, \( i = 1, \ldots, n \)
- \( \phi D_i \) duration (hours) of scheduled blackout when \( \Phi_i = 0 \), for HF \( i \), \( i = 1, \ldots, n \)
- \( \psi F_i \) mean frequency (hours) of random blackouts when \( \Psi_i = 0 \), for HF \( i \), \( i = 1, \ldots, n \)
- \( \psi D_i \) mean duration (hours) of random blackout when \( \Psi_i = 0 \), for HF \( i \), \( i = 1, \ldots, n \)
- \( loc_i \) binary parameter that is 1 if HF \( i \) does not have a local technician and 0 if it does, for \( i = 1, \ldots, n \)

NB: \( \eta \) and \( h \) were previously denoted with \( P \) and \( H \), respectively, in Chapter 5 and in Bradley et al., 2014 [19].

**OPT Model Decision Variables:**
- \( C_i \) number of concentrators needed at HF \( i \), for \( i = 1, \ldots, n \)
- \( A_i \) binary variable taking value of 1 if HF \( i \) should install an alternative energy source for concentrators, and 0 otherwise, for \( i = 1, \ldots, n \)
Costing and other related parameters:

- \( m \) maximum allowable unmet oxygen demand (% of total demand); Obj 1 only
- \( b \) budget available for oxygen technology and support system; Obj 2 only
- \( o \) capital cost of an oxygen concentrator
- \( f \) capital cost of a 5-way flow splitter
- \( a_i \) capital cost of alternative energy technology pre-selected for HF \( i, i = 1, \ldots, n \)
- \( t_I \) initial user and technician training cost (calculated on a per concentrator basis)
- \( t_A \) annual refresher technician and user training cost per HF
- \( l_H \) technician labour cost per hour
- \( r \) cost per repair
- \( l_T \) cost of technician transport per repair at a rural HF
- \( l_F \) hours of labour per repair
- \( l_P \) hours of labour per PM check
- \( p_f \) frequency of PM checks per machine per year
- \( w \) wattage of oxygen concentrator
- \( g \) cost per kWh of grid electricity
- \( \rho_u \) case fatality rate for patients who did not receive any oxygen treatment
- \( \rho_{pt} \) case fatality rate for patients who received partial oxygen treatment
- \( \rho_{ft} \) case fatality rate for patients who received full oxygen treatment

Parameters computed through SIM model:

- \( D_{tot} \) total oxygen demand (L) across all HFs over simulation period
- \( U_i \) unmet oxygen demand (L) at HF \( i \) over simulation period, for \( i = 1, \ldots, n \)
- \( U_{tot} \) total unmet oxygen demand (L) across all HFs over simulation period
- \( U_{prop} \) proportion of total oxygen demand that is unmet (\( U_{tot} / D_{tot} \))
- \( U_{max} \) maximum allowable unmet demand (L)
- \( R_i \) number of concentrator repairs at HF \( i \) over simulation period, \( i = 1, \ldots, n \)
- \( E \) total kWhs consumed across all HFs to operate concentrators (when demand existed)
- \( A_H \) total hours of alternative energy used to provide oxygen, \( \forall \) HFs where \( \Lambda_i = 1 \)
- \( A_L \) total L oxygen supplied when using alternative energy source, \( \forall \) HFs where \( \Lambda_i = 1 \)
- \( P_{FT} \) number of patients across all HFs who received full oxygen treatment during simulation period
- \( P_{PT} \) number of patients across all HFs who received partial oxygen treatment during simulation period
- \( P_{NT} \) number of patients across all HFs who did not receive oxygen treatment during simulation period
7.4 OPT Model Mathematical Formulation

As described in the OxOpt overview of section 7.1, there are two objective functions that a user can choose from.

7.4.1 Objective 1: Minimize total cost (subject to a limit on unmet oxygen demand)

\[
\begin{align*}
\text{minimize} & \quad \text{total cost} + K_1 \cdot \max(0, U_{tot} - U_{max}) \\
\text{subject to} & \quad (A_i + \Phi_i + \Psi_i) \leq 2 \quad i = 1, \ldots, n \\
& \quad C_i \in \text{int} \quad i = 1, \ldots, n \\
& \quad A_i \in [0, 1] \quad i = 1, \ldots, n \\
\end{align*}
\]

where:

\[
\text{total cost} = \text{cap cost} + \text{op cost}
\]

\[
U_{max} = m \cdot D_{tot}
\]

and K_1 is a sufficiently large scaling factor such that a penalty is incurred for exceeding the desired level of unmet demand. The first constraint ensures that an alternative energy source will not be recommended for any health facility that is not subject to scheduled or random blackout periods.

Total cost is a function of capital costs (one-time fixed costs for implementing the proposed solution) and operating costs (mostly determined through simulating the proposed solution over the desired simulation period). Capital costs include equipment costs (concentrators and alternative energy sources) and an initial capital investment in user and technician training, as follows:

\[
cap cost = \sum_{i=1}^{n} (C_i \cdot (o + f + t_I) + a_i) \\
\]

(7.2)

where \(a_i\) is dependent on \(C_i\) and is determined via a lookup table (see Table 4.4).

Operating costs include equipment repairs and regular preventive maintenance (including parts and labour, with extra transportation costs incurred for repairs done at rural facilities), annual refresher training for users and technicians, and electricity costs to operate oxygen concentrators. These costs are aggregated together over the entire analysis period as follows:

\[
\text{op costs} = \sum_{i=1}^{n} (r + l_T \cdot l_H) R_i + \sum_{i=1}^{n} l_T \cdot R_i \cdot \text{loc}_i + \sum_{i=1}^{n} (C_i \cdot l_P \cdot l_H \cdot pf \cdot y) + n \cdot t_A \cdot y + E \cdot g 
\]

(7.3)

An estimate of annual operating costs can be computed as: \(\text{op costs}/y\). Amortized capital expenses would be \(\text{cap costs}/y\) per year, assuming \(y\) represents the expected equipment lifespan.
7.4.2 Objective 2: Minimize unmet oxygen demand (subject to a budget constraint)

\[
\begin{align*}
\text{minimize} & \quad U_{\text{prop}} + K_2 \cdot \max(0, \text{total cost} - b) \\
\text{subject to} & \quad (A_i + \Phi_i + \Psi_i) \leq 2 \quad i = 1, \ldots, n \\
& \quad C_i \in \text{int} \quad i = 1, \ldots, n \\
& \quad A_i \in [0, 1] \quad i = 1, \ldots, n \\
\end{align*}
\]

where:

\[
U_{\text{prop}} = \frac{U_{\text{tot}}}{D_{\text{tot}}}
\]

and \(K_2\) is a sufficiently large scaling factor such that a penalty is incurred for exceeding the desired budget. \(U_{\text{tot}}\) and \(D_{\text{tot}}\) (and consequently \(U_{\text{prop}}\)) are determined through simulation.

7.5 Cost-benefit Analysis

The following cost-benefit outcomes are also computed by the OxOpt model:

Cost per child treated (\$/child treated):

\[
\$\text{/child treated} = \frac{\text{total cost}}{P_{FT}}
\]

Number of lives saved (\(LS\)):

\[
LS = (P_{FT} + P_{PT} + P_{NT}) \times \rho_u - (P_{FT}\rho_t + P_{PT}\rho_p + P_{NT}\rho_u)
\]

where \(\rho_t\) and \(\rho_u\) are user-defined case fatality rates for patients treated with oxygen and not treated with oxygen, respectively. The case fatality rate for patients partially treated, \(\rho_p\), is estimated in the model by interpolation between these two given fatality rates.

Cost per life saved (\$/life saved):

\[
\$\text{/life saved} = \frac{\text{total cost}}{LS}
\]

Cost per disability-adjusted life-year averted (\$/DALY):

\[
\$\text{/DALY} = \frac{\text{total cost}}{v \cdot LS}
\]

where \(v\) is the value of a death in DALYs. In Duke et al. [41] an infant death is assumed to have a value of 33 DALYs; this is the default value used in the model.
Chapter 7. Putting Supply and Demand Together: Technical Description of the OxOpt Model

7.6 OPT Model Solver: The Genetic Algorithm

7.6.1 Genetic algorithm overview

The genetic algorithm (GA) is a heuristic optimization method that is based on the principles of natural selection, the process that drives biological evolution. An initial population of potential solutions – or ‘individuals’ – is created, and the performance – or ‘fitness’ – of each solution is measured through the value of an objective function. Over successive generations, this population is repeatedly modified according to probabilistic genetic rules. The algorithm selects the fittest individuals to be ‘parents’ and – through mating, crossover and mutation – uses them to produce the ‘children’ of the next generation. This process of ‘evolution’ effectively guides the search towards an optimal solution [26, 85, 88].

Genetic algorithms are highly relevant for a wide variety of real-world engineering and life sciences problems because they can handle dynamic components and non-linear objective functions and constraints [26, 85, 112].

7.6.2 Choice of GA for the OxOpt model

The genetic algorithm was chosen for the OxOpt model because it can accommodate problems with large complex solution spaces where the objective function is discontinuous, non-differentiable, stochastic, or highly non-linear [88]. The GA can also address integer programming problems (i.e., where solution components are restricted to be integer-valued), another characteristic of the OxOpt model. Compatibility and integration with the SIM component already developed in Matlab was another key criteria and the ultimate deciding factor; the GA is the only optimization solver for non-smooth problems available in the Matlab programming environment that can easily handle integer constraints [87].

As will be shown in section 7.6.5, an added advantage of using a GA with Monte-Carlo-like simulations is that efficiencies in processing time can be achieved by exploiting the GA’s repeated evaluations of individual solutions [26, 84, 85].

The next three sections describe techniques and experimental work conducted to configure and improve the performance of the GA, specifically: (1) design of experiment for parameter value selection; (2) a solution space reduction technique; and (3) computation time reduction techniques.

7.6.3 GA parameter selection - Design of experiment

There are a number of configurable parameters that guide how the genetic algorithm chooses ‘parents’ from a population of solutions, creates ‘children’ from these parents for the next generation, and decides when to terminate the search (i.e., when a sufficiently ‘optimal’ solution has been achieved). The choice of parameter values can have an impact on the algorithm’s performance and efficiency so it is important to investigate the influence of different parameter selections on algorithm outcomes [112]. The process of tuning parameter values requires some experimentation and typically results in a compromise between processing time and solution quality [112].

Design of Experiments (DOE) – a systematic method to determine the relationship between factors affecting the output of a process – can be used to determine optimal GA parameter values [111]. A full-factorial DOE would test every combination of parameters at every level in order to observe parameter influence and interactions. This approach however, is very computationally expensive. Other approaches such as Latin Hypercubes, one-factor-at-a-time, and orthogonal array designs can be used to strategically
select a sample of experiments to gain intuition. For example, Bilton [11] used a one-factor-at-a-time approach to configure GA parameters for a photovoltaic reverse osmosis system optimization model. With this approach one factor is varied while all others are kept fixed, and then the next factor is tested in a similar fashion until all parameters have been tested. Limitations of this approach are that it is difficult to estimate factor effects or explore interaction effects [111], and the order chosen to test parameters could influence the outcome. An orthogonal array design is a subset of a full-factorial design selected to maintain orthogonality between factors. As a result, it is a more balanced experiment than the one-at-a-time method and is much more efficient than the factorial approach.

For the OxOpt model, an orthogonal array DOE was chosen to determine appropriate settings for four configurable GA parameters: population size, elite count, crossover fraction, and number of stall generations (‘stall count’). A more complete write-up of the methods, results and discussion for this experiment, including additional background literature on the effect of population size specifically, is provided in Appendix C.

The first three parameters affect the composition of future generations, whereas the fourth parameter affects the stopping point for the algorithm (detailed parameter descriptions are provided in Table 7.1). A total of 16 experiments tested each factor at four different levels, as shown in Table 7.2. A full-factorial DOE in this case would have required 16 times more experiments and thousands of extra hours of processing time.

Table 7.1: Genetic algorithm parameters to be chosen through experimentation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description and Justification for Test Levels</th>
<th>Test Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>Number of individual solutions at each generation. Should be at least equal to the number of decision variables. Increasing population size enables the GA to search more solutions but increases processing time</td>
<td>1, 2, 3 or 4 × number of decision variables$^a$</td>
</tr>
<tr>
<td>Elite count</td>
<td>Percentage of individuals with the best fitness values that automatically survive to the next generation. Should be at least 1 to ensure the best fitness value can only improve. High elite count may cause certain individuals to dominate future generations and allows for less random mutation.</td>
<td>10%, 20%, 30% or 40% (of population size)</td>
</tr>
<tr>
<td>Crossover fraction</td>
<td>Fraction of individuals in the next generation (other than elite children) that are created by crossing over of two parents. Whatever is not an elite or crossover child will be a mutated child. Should never be 0 or 1 as some crossover and some mutation is desired. Entire range within these limits is worth exploring.</td>
<td>0.2, 0.4, 0.6, or 0.8</td>
</tr>
<tr>
<td>Stall count</td>
<td>The algorithm stops when the relative change in the average of the best fitness function values over stall count generations is less than a specified tolerance ($\leq 0.5%$ in this experiment). A low stall count may end processing prematurely, but a high stall count increases processing time, sometimes without achieving more optimal results.</td>
<td>10, 20, 30 or 40</td>
</tr>
</tbody>
</table>

$^a$ The number of decision variables in the OxOpt model is always double the number of health facilities being modeled. For this experiment of 5 health facilities, the number of decision variables is 10.
Table 7.2: Orthogonal array experimental design for genetic algorithm parameter selection.

<table>
<thead>
<tr>
<th>Exp. No.</th>
<th>Population Size</th>
<th>Elite Count(^a)</th>
<th>Crossover Fraction</th>
<th>Stall Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>10</td>
<td>0.2</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>20</td>
<td>0.4</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>30</td>
<td>0.6</td>
<td>30</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>40</td>
<td>0.8</td>
<td>40</td>
</tr>
<tr>
<td>5</td>
<td>20</td>
<td>10</td>
<td>0.4</td>
<td>30</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
<td>20</td>
<td>0.6</td>
<td>40</td>
</tr>
<tr>
<td>7</td>
<td>20</td>
<td>30</td>
<td>0.8</td>
<td>10</td>
</tr>
<tr>
<td>8</td>
<td>20</td>
<td>40</td>
<td>0.2</td>
<td>20</td>
</tr>
<tr>
<td>9</td>
<td>30</td>
<td>10</td>
<td>0.6</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>30</td>
<td>20</td>
<td>0.8</td>
<td>20</td>
</tr>
<tr>
<td>11</td>
<td>30</td>
<td>30</td>
<td>0.2</td>
<td>30</td>
</tr>
<tr>
<td>12</td>
<td>30</td>
<td>40</td>
<td>0.4</td>
<td>40</td>
</tr>
<tr>
<td>13</td>
<td>40</td>
<td>10</td>
<td>0.8</td>
<td>30</td>
</tr>
<tr>
<td>14</td>
<td>40</td>
<td>20</td>
<td>0.2</td>
<td>40</td>
</tr>
<tr>
<td>15</td>
<td>40</td>
<td>30</td>
<td>0.4</td>
<td>10</td>
</tr>
<tr>
<td>16</td>
<td>40</td>
<td>40</td>
<td>0.6</td>
<td>20</td>
</tr>
</tbody>
</table>

\(^a\) Percentage of population size.

The experiment was conducted for a hypothetical scenario consisting of 5 health facilities with patient admissions ranging from 250 to 2000 annually (other scenario characteristics are shown in Table 7.3). The outcomes of interest were the objective function value (i.e., total system cost) as a performance measure and computation time as an efficiency measure. Each case was run three times and averaged due to the stochastic nature of the SIM model and random behaviour of the GA.

Based on the results of the DOE, the final parameter selections are provided in Table 7.4. Note that for scenarios with more than 5 health facilities, population size will be scaled appropriately, as described in Appendix C.

Table 7.3: Scenario details for genetic algorithm parameter selection experiment.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Health Facility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Annual child admissions</td>
<td>2000</td>
</tr>
<tr>
<td>Concentration of admissions in high season</td>
<td>45%</td>
</tr>
<tr>
<td>High season duration</td>
<td>3 months</td>
</tr>
<tr>
<td>Hypoxaemia prevalence</td>
<td>40%</td>
</tr>
<tr>
<td>Electricity available per day (h)</td>
<td>22</td>
</tr>
</tbody>
</table>
Table 7.4: Selected genetic algorithm parameter values for all future case studies.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>$1 \times$ number of decision variables</td>
</tr>
<tr>
<td>Elite count</td>
<td>20% (of population size)</td>
</tr>
<tr>
<td>Crossover fraction</td>
<td>0.6</td>
</tr>
<tr>
<td>Stall count</td>
<td>10</td>
</tr>
</tbody>
</table>

7.6.4 Reducing the solution space: Setting upper bounds for decision variables

Setting lower and upper bounds for each element of the solution vector is another important step in the optimization setup because it defines the boundaries and size of the solution space. The smaller the solution space, the more efficient the algorithm will be at searching the space for the optimal solution.

For the OxOpt model, the number of possible solutions for any given scenario is a function of the number of health facilities being analyzed, $n$, and the maximum number of concentrators expected for each health facility, $C_{max}$, according to the formula $C_{max} \times 2^n$. If, for example, the maximum number of concentrators for a 5-health facility problem is conservatively estimated to be 5 for each facility, the size of the solution space would be $5^5 \times 2^5 = 100,000$; each facility has 5 possible options for number of concentrators ($C_i$) and two possible options (0 or 1) for the binary variable affecting the alternative energy decision ($A_i$). The solution space can be reduced considerably if a more accurate estimation of the maximum number of concentrators can be found.

The SIM component of the OxOpt model (described in section 7.2) can be used in isolation to better estimate the maximum number of concentrators that might be needed at any given health facility. Since the SIM model provides hourly oxygen demand data, the output can be searched for the maximum demand level ever reached, which in turn will indicate the maximum number of concentrators needed. If it is determined that the most number of concentrators needed at each of the 5 health facilities from the example above is 5, 5, 3, 3, and 3, respectively, then the solution space for this scenario would be reduced to $5^2 \times 3^3 \times 2^5 = 21,600$ - a reduction of over 78%.

This solution space reduction technique is performed as an initial step when setting up the OxOpt model for all case study scenarios.

7.6.5 Reducing computation time: Exploiting GA repetitiveness for computation efficiency

To further optimize the performance of the genetic algorithm, additional steps and experimentation were undertaken to improve efficiency and processing time. With the GA approach the best-performing individuals can appear many times in successive generations whereas bad ones are readily eliminated by ‘natural selection’ [85]. As demonstrated by Marseguerra et al. [26, 84, 85] in their work on optimizing the design, operation and reliability of complex systems and industrial plants, when Monte-Carlo-like simulations are combined with a genetic algorithm, this repetitive behaviour can be exploited to reduce unnecessary processing time. This occurs in two ways:

- **Reducing the number of simulation iterations, $j$, when an individual is evaluated:** When an individual is evaluated during the GA search, it requires running the Monte Carlo simulation
for a given number of iterations and computing mean values for outcome measures to calculate
the objective function value (i.e., the individual’s fitness). Whenever an individual is re-visited
by the GA search, the objective function evaluations from the Monte Carlo simulation can be
accumulated in an archive. Individuals need only be evaluated by a limited number of Monte
Carlo iterations since promising solutions that survive to future generations will be repeatedly
evaluated, growing the archive and building significance of the results. By the same logic, time is
not wasted on excessive Monte Carlo iterations of ‘bad’ individuals that are selected only a small
number of times during the search [85].

• Limiting the number of times an individual is evaluated (archive size): When the same
individual is evaluated several times, building the archive as described above, at some point, no
further computations will be required for a given individual. Output values stored in the archive
can be averaged and those mean values used for all future evaluations of that particular individual,
circumventing the need to run the simulation again, thus reducing unnecessary processing time.

For these two strategies to be effectively implemented for the OxOpt model, the following two ques-
tions had to be answered via experimentation: 1) What is the fewest number of simulation iterations
that should be conducted for each individual evaluation? and 2) How many evaluations should be com-
piled in the GA solution archive for any given individual? The following subsections summarize the
experiments and results that answer these questions. A more complete write-up of the methods, results
and discussions for these experiments is provided in Appendix D.

1) Determining the minimum number of simulation iterations

An experiment consisting of 5 randomly generated solutions (‘trials’) for a hypothetical scenario con-
sisting of 5 health facilities was conducted to determine a minimum number of simulation iterations in
order to reduce simulation computation time while achieving statistical equivalence to a higher (more
computationally intensive) number of iterations. Only the SIM component of the OxOpt model was
used for this experiment. Mean results for simulations consisting of 3, 5, 10, 25, and 50 iterations were
compared to each other and to the ‘true’ mean (assumed to be the mean achieved from 500 iterations)
across 9 different output measures (total cost, satisfied demand, unsatisfied demand, unmet proportion
of demand, number of repairs, number of patients treated, partially treated, and untreated, and lives
saved). Complete experimental results are provided in Appendix section D.1.

Across all 5 trials and 9 different output measures, there was no significant difference between the
results obtained for simulations with 5 iterations versus those with 50 iterations ($p<0.05$). Furthermore,
there was less than a 0.5% difference in total cost (the key objective function measure) across all trials
when using 5 iterations compared with the ‘true’ mean. Based on this experiment, it was concluded that
5 simulation iterations would be sufficient when processing the SIM model embedded within the OxOpt
model.

2) Determining how many solution evaluations to keep in the GA archive

This experiment was conducted to determine how many solution evaluations should be compiled in
the GA solution archive before no added benefit is achieved by additional solution evaluations. Two

---

3The same scenario used for the genetic algorithm parameter selection experiments presented in section 7.6.3; see Table
7.3 for details.
scenarios consisting of five and six health facilities were used. For each scenario, the full OxOpt sim-opt process was run with solution archive sizes of 10, 25 and 50. The outcomes of interest were the objective function value (i.e., total system cost) as a performance measure and computation time as an efficiency measure. Each case was run three times and averaged due to the stochastic nature of the SIM model and random behaviour of the GA. Complete experimental results are provided in Appendix section D.2.

It was found that archiving 10 solution evaluations in the GA solution archive saves considerably on processing time and still leads to optimal solutions. Using an archive size of 10, objective function values for optimal solutions were less than 1% different compared to an archive size of 25, and less than 3% different compared to an archive size of 50. Yet, processing times were up to 1.7 and 2.0 times longer for archive sizes of 25 and 50, respectively. Processing time did not vary directly with archive size; the algorithm tended to converge before solutions reached a high number of archived evaluations. In fact, there was no significant difference ($p > 0.1$) in percent coverage of the solution space or number of generations to convergence when using an archive size of 10 versus 25 or 50 (see Appendix section D.2 for more details). Based on these results, an archive size of 10 will be used in all future case studies.

### 7.7 Summary of OxOpt Processing Steps

A detailed flowchart of the OxOpt model processing steps is provided in Fig. 7.4.
Figure 7.4: Flow diagram of OxOpt model process. See section 7.3 for parameter definitions. HF = health facility; HFSM = Health Facility Systems Model; TSM = Technology Systems Model.
Chapter 8

The Gambia Case Study: Using OxOpt for Oxygen Technology Planning

8.1 Introduction

This chapter presents the case study of applying the OxOpt model to The Gambia to improve oxygen supplies for the treatment of childhood pneumonia. Following the framework presented in Chapter 6, a situational analysis was conducted to better understand the Gambian context (i.e., health systems-level background, health-facility-level characteristics, realistic costing data, etc.) and to determine appropriate input values for the model. This process included a literature search for relevant data, consultation with local experts, and prospective collection of field data. This situational analysis is summarized in section 8.2. An options analysis determining the appropriate alternative energy source for each health facility in the model and their estimated costs is presented in section 8.3. All model input values for The Gambia case study are summarized in section 8.4.

In section 8.5, the OxOpt model is used to determine optimal oxygen technology recommendations for The Gambia for several scenarios. The scenarios aim to capture many of the challenges faced in The Gambia, such as: limited resources, poor electricity supply, and geographic inequalities in resource allocation. The chapter concludes in section 8.6 with a discussion of the scenario results.

8.2 Situational Analysis

8.2.1 Health system

The Gambia is a low-income country in West Africa with a gross domestic product (GDP) of US $851 million and a gross national income (GNI) per capita of US $1,580. The Gambia has a population of about 2 million, 48% of which lives below the national poverty line. Fifty-seven percent of the population is concentrated around urban and per-urban centres. Life expectancy in The Gambia is only 60 years, with 46% of the population under the age of 15 [130,154].
The Gambia public health care delivery system has three tiers, comprising tertiary central hospitals, secondary care facilities (‘minor’ and ‘major’ health centres) and primary village-based services, or community health posts [61,155]. It is the major health centres and hospitals that should have the capability to deliver medical oxygen, and thus these are the facilities of most concern for this research. There are also a number of privately run clinics and health-focused non-governmental organizations (NGOs) operating in The Gambia, as well as a large traditional healing sector [155], but these are considered outside the scope of this research.

As shown in Fig. 8.1, the country is divided into five administrative regions and two municipalities [155]. The municipalities and the Western region are the most densely populated areas, and the Lower River region is the least populated. There are five government hospitals, three of which – the Royal Victoria Hospital (RVH), Farafenni Hospital and Bansang Hospital – are main referral hospitals (RVH being the final referral centre in the country). The RVH is located in the capital city of Banjul, which has a population of 31,300 [51]. There are also six major health centres, relatively evenly distributed across the country. Highly populated village regions where major health centres are located include: Brikama (population 699,704), Kuntaur (population 99,108), and Basse (population 239,916) [51].

The health referral system is a hierarchical system, meaning there are never referrals within a level, even if a similar facility may be better equipped or geographically closer than the identified referral centre. For example, major health centres serve as the referral point for minor health centres for services such as obstetric emergencies and essential surgical services. In practice however, the referral systems are not fully functional, due to inadequate staffing and lack of appropriate equipment and transport [155].

In general, there is an unmet need for effective child health services due to lack of basic equipment and supplies, acute shortages of skilled health professionals, a weak referral system, and inadequate financial resources. Health facilities are stretched beyond their available resources, and national public health programmes are grappling with how best to achieve high coverage rates to deal with the most pressing health problems faced by the population [101].

8.2.2 Pneumonia burden and oxygen availability

Every year in The Gambia, almost 6,000 children die below the age of five [110]. Although the under-5 mortality rate dropped from about 119 per 1000 live births in 2000 to 69 in 2015, this rate of decline was not sufficient to achieve the Millennium Development Goal for child mortality [110,130,154]. There also exists huge inequalities within the country in terms of disease morbidity and mortality; for example, under-five mortality is three-fold higher in the Lower River Region (region D in Fig. 8.1) than in the municipality of Banjul (region A) [50].

In 2015, an estimated 766 children died from pneumonia in The Gambia, accounting for about 14% of under-five deaths in the country [110]. In order to reduce mortality from pneumonia, the goal is to increase access to oxygen therapy for those patients who are hypoxaemic. Studies have shown the prevalence of hypoxaemia among child pneumonia admissions in The Gambia to be between 6% and 19% [67,70,71,96,136], with the lower range found at the Royal Victoria hospital [136] and the higher end being measured in Basse, the furthest interior major health facility [70,71]. For this case study, a hypoxaemia prevalence of 12% as found by Junge et al. [67] is used.¹

The rate of pneumonia and hypoxaemia admissions is not consistent throughout the year in The Gambia. The country has a dry unimodal climate with a single 4-month rainy season from about July

¹Sensitivity to hypoxaemia prevalence was explored in Chapter 5.
Chapter 8. The Gambia Case Study: Using OxOpt for Oxygen Technology Planning

Figure 8.1: Map of The Gambia showing locations of public hospitals (H) and major health centres (⊕). The country is divided into two municipalities (Banjul and Kanifing) (A) and five administrative regions; Western (B), North Bank (C), Lower River (D), Central River (E), and Upper River (F).

to October. Paediatric pneumonia has been shown to be seasonal, with admissions peaking around August and September in the middle of rainy season [25,67,138,139]. Based on studies that provided a breakdown of number of admissions per month [67, 138], it was found that about 45% of cases arrived during the 4-month rainy season.²

In 2009, Hill et al. [61] conducted an assessment at every government hospital and major health centre in The Gambia (n = 12) to get a more detailed picture of the pneumonia burden and oxygen availability across the country. About 3,100 pneumonia cases were seen across all health facilities in a 1-year period, about 62% of which presented to hospitals and 38% to major health centres (Table 8.1). These data are used as the annual pneumonia admission rates for each health facility.

In terms of oxygen supply, they found that five health facilities (one hospital and four health centres) had no oxygen supply at all, and most others had fair to good supply (Table 8.1). At that time, oxygen was being provided via cylinders or oxygen concentrators with three facilities having a mix of both. This oxygen availability information is used to inform the ‘status quo’ scenario, to which all OxOpt recommendations are compared in section 8.5.

Oxygen therapy does not guarantee survival for pneumonia patients, it only helps reduce the risk of death. Pneumonia case fatality rates for patients with and without access to oxygen treatment are needed in order to estimate the number of lives saved by providing better access to oxygen. The best available evidence demonstrating a reduction in mortality through the provision of oxygen is from a

²Sensitivity to proportion of cases in high season was explored in Chapter 5
study in Papua New Guinea (PNG) which reported a 35% reduction in case fatality rate (CFR) (from 5.0% to 3.2%) before and after the introduction of oxygen systems in five hospitals [41]. In Malawi, pneumonia mortality dropped from 15.2% to 4.5% between 2001 to 2012 in hospitals participating in their Child Lung Health Programme, which included improved use of oxygen therapy. The CFRs in both of these cases are low compared to mortality rates observed in The Gambia, ranging from about 8% to 15% for very severe hypoxaemic pneumonia [25, 67, 71, 96, 114, 136, 140] - and in most of these studies, oxygen was available to children included in the study. Case fatality rate without oxygen in The Gambia is unknown. Given the limited available evidence for The Gambia, it is assumed that a similar reduction as that observed in PNG (i.e., 35%) might be expected in The Gambia with improved access to oxygen, despite the initial CFR being much higher. Thus, for this case study it is assumed that the CFRs $\rho_u$, $\rho_p$, and $\rho_t$ are 15%, 12.5% and 10%, respectively, which corresponds to a mortality risk reduction of 33%. Sensitivity of this assumption is tested in section 8.5.3.

Table 8.1: Pneumonia case burden and oxygen availability across hospitals and major health centres in The Gambia. Baseline situation as of 2009. Data adapted from Hill et al. (2009) [61].

<table>
<thead>
<tr>
<th>Hospitals</th>
<th>Total Under-5 Admissions $^a$</th>
<th>Pneumonia Under-5 Admissions $^b$</th>
<th>Oxygen Availability</th>
<th>Reliability of supply $^d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Royal Victoria Hospital</td>
<td>6,303</td>
<td>653</td>
<td>✓       ✓</td>
<td>Good</td>
</tr>
<tr>
<td>Serekunda Hospital</td>
<td>1,671</td>
<td>519</td>
<td>✓       None</td>
<td>None</td>
</tr>
<tr>
<td>Sulayman Junkung Hospital, Bwiam</td>
<td>299</td>
<td>46</td>
<td>✓       ✓</td>
<td>Good</td>
</tr>
<tr>
<td>AFPRC Hospital, Farafenni</td>
<td>1,100</td>
<td>142</td>
<td>✓       ✓       ✓</td>
<td>Fair</td>
</tr>
<tr>
<td>Bansang Hospital</td>
<td>1,920</td>
<td>564</td>
<td>✓       ✓       ✓</td>
<td>Excellent</td>
</tr>
<tr>
<td><strong>Major Health Centres</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fajikunda</td>
<td>975</td>
<td>303</td>
<td>✓       None</td>
<td>None</td>
</tr>
<tr>
<td>Brikama</td>
<td>2,646</td>
<td>365</td>
<td>✓       None</td>
<td>None</td>
</tr>
<tr>
<td>Essau</td>
<td>1,213</td>
<td>169</td>
<td>✓       ✓       ✓</td>
<td>Fair</td>
</tr>
<tr>
<td>Soma</td>
<td>1,455</td>
<td>153</td>
<td>✓       None</td>
<td>None</td>
</tr>
<tr>
<td>Kuntaur</td>
<td>225</td>
<td>78</td>
<td>✓       None</td>
<td>None</td>
</tr>
<tr>
<td>Basse</td>
<td>556</td>
<td>100</td>
<td>✓       ✓       ✓</td>
<td>Poor</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>18,363</td>
<td>3,092</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^a$ Based on in-patient registers over a 12-month period; $^b$ Defined as any recorded diagnosis of ‘acute respiratory infection (ARI)’, ‘acute lower respiratory infection (ALRI)’, or ‘pneumonia’; $^c$ Cylinders typically main source, but empty at time of assessment visit; $^d$ Excellent = 24-h supply, Good = oxygen available at most times (with occasional interruptions), Fair = oxygen available only at some times of day (e.g., when generator is on), Poor = oxygen not available at time of assessment visit; AFPRC = Armed Forces Provisional Ruling Council.

### 8.2.3 Electricity availability and cost

Electricity generation in The Gambia is predominantly fossil-fuel based; heavy fuel oil is used in the Greater Banjul Area, and diesel oil is used for provincial operations. All the fuel used in electricity production is imported, which not only imposes a great cost to the economy due to the foreign exchange involved, but also means the country is vulnerable to the price volatility of oil [125].

The energy sector in The Gambia faces many challenges: lack of fuel diversity; high cost and irregular
supply of fuel for electricity generation; an inadequate transmission and distribution network; operational inefficiencies at National Water and Electricity Company (NAWEC) – the main utility company – resulting in transmission and distribution losses; weak regulatory and enforcement capacity; and poor reliability of electricity supply from the grid. Due to these factors, The Gambia has some of the highest electricity rates in the sub-region (between US $0.24 and $0.30 per kWh), with prices up to 2.6 times that of neighbouring West African countries [125].

The Government launched a rural electrification project in 2007 that built new power plants in all the major provincial towns, however all the generators were diesel units. Electricity services were significantly improved with most localities experiencing in excess of 12 hours of electricity per day - 6 hours in the morning and 6 hours in the evening.

In order to gain a better understanding of power availability in the public health system for this research, seven geographically representative health facilities were prospectively monitored between 2009 and 2011. An LS164 power interruption logger (Electrocoder, Newtownabbey, UK) was plugged into an electrical outlet in the paediatric ward of each health facility for a period of at least one week (range: 8 days to 9 weeks). The logger recorded the time at which a power outage occurred as well as the duration of the outage until power was restored. For each health centre, the following were computed: total percentage of time power was available during the monitoring period, mean number of interruptions per day, mean interruption duration, and maximum interruption duration. During the site visits, it was also determined whether the facility experienced electricity rationing by NAWEC, meaning electricity is only supplied for scheduled portions of the day, and whether there was a generator on site. Results for three of these facilities were previously published [17].

Power availability measures are summarized in Table 8.2. Four health facilities were subject to scheduled grid blackout periods, and all but one health facility had a generator. Since the logger could not distinguish between grid or generator power, it was impossible to determine what proportion of power ‘on’ time was due to grid or generator power. However, any power provided outside of the scheduled grid supply (in the case of Essau, Farafenni, and Bansang) would be supplied by a generator on an emergency as-needed basis. All 7 health facilities had power at least 50% of the time. The Royal Victoria hospital, the main referral hospital in the capital Banjul, had the highest availability (nearly 100%), followed by Brikama and Basse, which were both over 85%. All three of these facilities were not subject to scheduled grid blackout periods.

Table 8.3 summarizes additional power interruption characteristics across the seven health facilities monitored. Many interruptions were recorded as being only 1 to 2 seconds long, especially for the Essau and Basse health centres. These very short outages are likely due to fluctuations in voltage quality, whereby an instantaneous drop in voltage (down to 0 volts) is detected by the measurement device as an outage. Thus, the average number of 1 or 2 second interruptions per day is reported separately in Table 8.3 as a measure of power quality. Many interruptions were greater than 2 seconds but less than 10 seconds, representing true interruptions (i.e., not just a low-voltage condition) but not durations that would significantly interrupt oxygen supply. Again, Essau and Basse experienced the most interruptions of this duration (Table 8.3).

Mean interruption durations ranged from just under 5 min to 3 h 48 min. Mean interruption durations were computed with interruptions less than 10 seconds excluded since these very short interruptions skewed the average. However, even with interruptions less than 10 seconds excluded, lower mean values for Essau and Basse are likely due to high numbers of interruptions in the 10 to 30 second range, rather
than a more reliable power supply.

The longest power interruption observed was 13.5 hours at the Soma health centre, even though the longest expected interruption based on the NAWEC schedule should only be 7 or 8 hours. For all other health facilities, the maximum interruption duration was less than 7.5 hours, which is about the longest expected duration based on the NAWEC schedule. Generator power was likely used in the off-grid periods, shortening the window of time without power. It should be noted that Soma and Basse were monitored for a much greater time period than the other health centres, and thus the likelihood of capturing a long unexpected power outage during the monitoring period would have been higher.

Although power availability was over 50% for the health facilities on scheduled blackouts (Essau, Farafenni, Soma and Bansang), this does not necessarily mean that the 12-13 hours of scheduled grid power was 100% reliable and the remaining supply was due to the operation of a generator. Typically, the generator is operated during off-grid hours in emergency situations only. Power outages are common during scheduled grid time, the generator may or may not have been started during these times as well.

These data provide a representative sample of the patterns in electricity availability at health facilities across the country and are used for the options analysis in the next section as well as for health facility-specific input to the SIM component of the OxOpt model. For the health facilities that were not included in this study, observations from Hill et al. [61] are used as model inputs.

Table 8.2: Electricity availability in Gambian health facilities.

<table>
<thead>
<tr>
<th>Health Facility</th>
<th>Type</th>
<th>Available Sources</th>
<th>NAWEC Grid Electricity Schedule</th>
<th>Total time monitored (d, h)</th>
<th>Time power is ON (% total time monitored)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Royal Victoria Hospital</td>
<td>Hospital</td>
<td>✓</td>
<td>NA</td>
<td>8 d 19 h</td>
<td>99.5%</td>
</tr>
<tr>
<td>Brikama</td>
<td>Health Centre</td>
<td>✓</td>
<td>NA</td>
<td>9 d 12 h</td>
<td>90.8%</td>
</tr>
<tr>
<td>Essau a</td>
<td>Health Centre</td>
<td>✓</td>
<td>9 am b - 2 pm: 5 h 7 pm - 2 am: 7 h TOTAL: 12 h</td>
<td>12 d 22 h</td>
<td>56.6%</td>
</tr>
<tr>
<td>AFPRC Farafenni a</td>
<td>Hospital</td>
<td>✓</td>
<td>9 am b - 2 pm: 5 h 7 pm - 3 am: 8 h TOTAL: 13 h</td>
<td>12 d 2 h</td>
<td>51.3%</td>
</tr>
<tr>
<td>Soma a</td>
<td>Health Centre</td>
<td>✓</td>
<td>9 am b - 2 pm: 5 h 7 pm - 2 am: 7 h TOTAL: 12 h</td>
<td>56 d 11 h</td>
<td>54.5%</td>
</tr>
<tr>
<td>Bansang</td>
<td>Hospital</td>
<td>✓</td>
<td>10 am - 4 pm: 6 h 7:30 pm - 6:30 am: 11 h TOTAL: 17 h</td>
<td>8 d 3 h</td>
<td>63.6%</td>
</tr>
<tr>
<td>Basse</td>
<td>Health Centre</td>
<td>✓</td>
<td>NA</td>
<td>64 d 22 h</td>
<td>85.9%</td>
</tr>
</tbody>
</table>

a Previously published in Bradley et al. (2011) [17]; b Fridays generally begin at 10 am or later; NA = not applicable; NAWEC = National Water and Electricity Company of The Gambia.
Table 8.3: Power interruption characteristics in Gambian health facilities.

<table>
<thead>
<tr>
<th>Health Facility</th>
<th>Type</th>
<th>Mean no. interruptions per day (by duration)</th>
<th>Mean interruption duration (hh:mm:ss)</th>
<th>Max. interruption duration (hh:mm:ss)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1 - 2 s</td>
<td>3 - 10 s</td>
<td>&gt; 10 s</td>
</tr>
<tr>
<td>Royal Victoria Hospital</td>
<td>Hospital</td>
<td>1.4</td>
<td>0.1</td>
<td>1.6</td>
</tr>
<tr>
<td>Brikama</td>
<td>Health Centre</td>
<td>0.2</td>
<td>0.1</td>
<td>2.2</td>
</tr>
<tr>
<td>Essau</td>
<td>Health Centre</td>
<td>56.0</td>
<td>28.1</td>
<td>17.3</td>
</tr>
<tr>
<td>AFPRC Farafenni</td>
<td>Hospital</td>
<td>0.7</td>
<td>0.5</td>
<td>3.8</td>
</tr>
<tr>
<td>Soma</td>
<td>Health Centre</td>
<td>0.07</td>
<td>0.04</td>
<td>2.9</td>
</tr>
<tr>
<td>Bansang</td>
<td>Hospital</td>
<td>14.8</td>
<td>4.4</td>
<td>7.8</td>
</tr>
<tr>
<td>Basse</td>
<td>Health Centre</td>
<td>22.8</td>
<td>13.7</td>
<td>11.1</td>
</tr>
</tbody>
</table>

a Previously published in Bradley et al. (2011) [17]; b Interruptions ≤ 10s are excluded from this calculation.

8.3 Options Analysis: Appropriate Alternative Energy Options

Figure 4.5 and Table 4.4 were used to determine appropriate alternative energy options for each health facility in The Gambia case study. These choices are summarized in Table 8.4. No health facility had less than four hours of grid power, thus solar-power is not an energy option considered in this context. A ‘what-if’ scenario in section 8.5.5 explores at what price-point an off-grid solar option would be cost-effective given increasing kWh costs for two facilities (RVH and Basse).

Table 8.4: Summary of options analysis for appropriate alternative energy sources for each health facility in The Gambia.

<table>
<thead>
<tr>
<th>HF</th>
<th>Name</th>
<th>Type</th>
<th>Hours of grid available per day</th>
<th>Alternative energy source option</th>
<th>Alternative energy equipment cost</th>
<th>Region</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Banjul</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Western</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>North Bank</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lower River</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Central River</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Upper River</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Royal Victoria</td>
<td>Hospital</td>
<td>23</td>
<td>UPS</td>
<td>$4,000</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Serekunda</td>
<td>Hospital</td>
<td>16</td>
<td>BAT</td>
<td>$5,260</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Fajikunda</td>
<td>Health Centre</td>
<td>12</td>
<td>BAT</td>
<td>$5,500</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Brikama</td>
<td>Health Centre</td>
<td>22</td>
<td>BAT</td>
<td>$5,160</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Bwiam</td>
<td>Health Centre</td>
<td>12</td>
<td>BAT</td>
<td>$5,500</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Essau</td>
<td>Health Centre</td>
<td>12</td>
<td>BAT</td>
<td>$5,500</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>AFPRC Farafenni</td>
<td>Hospital</td>
<td>13</td>
<td>BAT</td>
<td>$5,500</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Soma</td>
<td>Health Centre</td>
<td>12</td>
<td>BAT</td>
<td>$5,500</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Kuntaur</td>
<td>Health Centre</td>
<td>12</td>
<td>BAT</td>
<td>$5,500</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Bansang</td>
<td>Health Centre</td>
<td>17</td>
<td>BAT</td>
<td>$5,260</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Basse</td>
<td>Health Centre</td>
<td>20</td>
<td>BAT</td>
<td>$5,160</td>
<td></td>
</tr>
</tbody>
</table>

UPS = uninterrupted power supply; BAT = grid-charged back up battery bank. a All cost estimates are per concentrator, except for the UPS which is for up to 5 concentrators.
8.4 Summary of *OxOpt* Model Inputs for The Gambia Case Study

Based on the situational and options analyses presented above, input values for all SIM model parameters are summarized in Table 8.5. Costing and other related parameters for the OPT model component are summarized in Table 8.6.

Model results will be sensitive to model input values. Sensitivity to hypoxaemia prevalence ($h_i$) and proportion of admissions in high season ($\eta_i$) was demonstrated in Chapter 5 and thus will not be explored further in this chapter. Demand threshold ($m$) and available budget ($b$) will vary depending on the scenario. Sensitivity to case fatality rates ($\rho_t$, $\rho_p$, and $\rho_u$) will be explored in section 8.5.3. All other inputs will be kept constant for the analyses in this chapter, unless otherwise specified for a ‘what-if’ scenario.
<table>
<thead>
<tr>
<th>Name</th>
<th>Banjul</th>
<th>Western</th>
<th>North Bank</th>
<th>Lower River</th>
<th>Central River</th>
<th>Upper River</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Royal Victoria</td>
<td>Serekunda</td>
<td>Fajikunda</td>
<td>Brakama</td>
<td>Brikama</td>
<td>Essau</td>
</tr>
<tr>
<td>Main referral hospital</td>
<td>Hospital</td>
<td>Health Centre</td>
<td>Health Centre</td>
<td>Hospital</td>
<td>Health Centre</td>
<td>Health Centre</td>
</tr>
</tbody>
</table>

### SIM - HFSM Input Parameters (all scenarios)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual child admission rate ( \lambda )</td>
<td>655 250 305 365 45 170 140 165 80 565 100</td>
</tr>
<tr>
<td>High season proportion ( \eta )</td>
<td>45% ^b</td>
</tr>
<tr>
<td>First month high season ( r_1 )</td>
<td>7 (July) ^b</td>
</tr>
<tr>
<td>Last month high season ( r_2 )</td>
<td>10 (October) ^b</td>
</tr>
<tr>
<td>Duration of ramp up/down period ( s_c )</td>
<td>30 days</td>
</tr>
<tr>
<td>Hypoanaemia prevalence ( h_0 )</td>
<td>12% ^c</td>
</tr>
<tr>
<td>Scheduled grid blackouts (SGB) ( \Phi )</td>
<td>1 ^d 1 ^d 1 ^d 1 ^d 0 ^e 0 ^e 0 ^e 1 ^e 0 ^e 0 ^e 1 ^e</td>
</tr>
<tr>
<td>Random grid outages (RGO) ( \Psi )</td>
<td>0 ^f 0 ^f 0 ^f 0 ^f 0 ^f 0 ^f 0 ^f 1 ^g 1 ^g 1 ^g 1 ^g</td>
</tr>
<tr>
<td>Frequency of SGBs ( q_{SGB} )</td>
<td>- - - - - - 12 ^i 12 ^i 12 ^i - 12 ^i -</td>
</tr>
<tr>
<td>Duration of SGBs ( d_{SGB} )</td>
<td>- - - - - - - - - - - - - - -</td>
</tr>
<tr>
<td>Mean frequency of RGOs ( q_{RGO} )</td>
<td>62 ^i 6 ^i 6 ^i 10.5 ^i 6 ^i - - - - - - - - - -</td>
</tr>
<tr>
<td>Mean duration of RGOs ( d_{RGO} )</td>
<td>0.5 ^i 2 ^i 3 ^i 1 ^i 3 ^i - - - - - - - - - -</td>
</tr>
<tr>
<td>Local tech, lic, (0years, 9000)</td>
<td>0 0 1 1 1 1 1 1 1 1 1 1</td>
</tr>
<tr>
<td>Alt Option</td>
<td>UPS</td>
</tr>
<tr>
<td>Max no. conc ^^</td>
<td>3 3 2 3 2 2 2 2 2 3 2</td>
</tr>
</tbody>
</table>

### SIM - TSM Input Parameters (status quo scenario only)

- No. concentrators: C
- Maximum energy source available: \( A \)
- Cylinders available: \( Y \)
Table 8.6: Costing and other related parameters for The Gambia case study. All costs in $USD.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Notes and Source(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum allowable unmet demand, $m$</td>
<td>10%, 20%</td>
<td>Relevant for Objective Function 1 only. Subject to specific analysis.</td>
</tr>
<tr>
<td>Available budget, $b$</td>
<td>$60,000</td>
<td>Relevant for Objective Function 2 only. Subject to specific analysis.</td>
</tr>
<tr>
<td>Capital cost of oxygen concentrator, $o$</td>
<td>$1,025</td>
<td>Mean cost from Bradley et al. (2016), includes shipping.</td>
</tr>
<tr>
<td>Capital cost of 5-way flowsplitter, $f$</td>
<td>$625</td>
<td>Costing data from contacts in The Gambia, includes shipping, unpublished.</td>
</tr>
<tr>
<td>Capital cost of alternative energy technology pre-selected for HF, $a$</td>
<td></td>
<td>Determined via lookup table; see Sec 4.4 for details.</td>
</tr>
<tr>
<td>Initial user and technician training cost (per concentrator), $t_i$</td>
<td>$1,000</td>
<td>See Sec 3.3 for justification</td>
</tr>
<tr>
<td>Annual refresher training cost (per health facility), $t_A$</td>
<td>$200</td>
<td>See Sec 3.3 for justification</td>
</tr>
<tr>
<td>Technician labour cost (per hour), $l_i$</td>
<td>$1.40</td>
<td>Costing data from contacts in The Gambia, unpublished.</td>
</tr>
<tr>
<td>Average cost per repair, $r$</td>
<td>$55</td>
<td>Bradley et al. (2015) (see Chapter 3)</td>
</tr>
<tr>
<td>Hours of labour (per repair), $l_R$</td>
<td>2</td>
<td>Bradley et al. (2015) (see Chapter 3)</td>
</tr>
<tr>
<td>Hours of labour (per PM check), $l_p$</td>
<td>0.5</td>
<td>Bradley et al. (2015) (see Chapter 3)</td>
</tr>
<tr>
<td>Frequency of PM checks (per concentrator per year), $P_f$</td>
<td>3</td>
<td>Bradley et al. (2015) (see Chapter 3)</td>
</tr>
<tr>
<td>Wattage of oxygen concentrator, $w$</td>
<td>350W</td>
<td>For Airsep Intensity 5L/min model</td>
</tr>
<tr>
<td>Cost per kWh of grid electricity, $g$</td>
<td>$0.28</td>
<td>Bradley et al. (2016), Howie et al. (2009)</td>
</tr>
</tbody>
</table>

Case fatality rates:

- Treated, $\rho_t$: 8% to 12%
- Partially treated, $\rho_p$: 9% to 16%
- Untreated, $\rho_u$: 10% to 20%

8.5 OxOpt Model Scenarios and Recommendations

In order to provide a baseline against which to compare the OxOpt model recommendations, a ‘status quo’ scenario was simulated for The Gambia over a period of five years (averaged over $j = 100$ iterations). Input data for this scenario, summarized in Table 8.5, are based largely on the 2009 survey of health facilities by Hill et al. [61] as well as observations from site visits. Capital equipment costs are included in the analysis (even though any existing concentrators were obviously already purchased) in order to measure the incremental costs of OxOpt model recommendations.
Next, two nation-wide analyses applying Objective 1 and 2 are presented in section 8.5.1. Then, in section 8.5.2 an ‘equity analysis’ presents four additional scenarios demonstrating different ways that health care equity might be considered when allocating resources to improve oxygen supply. Next, section 8.5.3 provides a sensitivity analysis of how estimates for number of lives saved are affected by input values for case fatality rates, $\rho_u$, $\rho_p$, and $\rho_t$. In sections 8.5.4 and 8.5.5, ‘what-if’ scenarios explore other hypothetical considerations when planning an oxygen technology strategy; namely, robustness of model recommendations to the potential effects of climate change, increased equipment lifespans beyond the default used, and conditions under which off-grid oxygen solutions would be more cost-effective than the recommended grid-tied systems.

8.5.1 National analysis

Introduction and scenario setup

The OxOpt model was run using Objective 1, which aims to minimize the cost to achieve a minimum threshold of oxygen demand - in this case 80% was chosen. Next, the OxOpt model was run using Objective 2, with a maximum budget, $b$, set to US $60,000 over 5 years, which represents double the current estimated cost. Equipment lifespans are assumed to be five years for both scenarios; thus all simulations are run over a 5-year time horizon.

Results

Table 8.7 shows the solutions (i.e., decision variable values) obtained when running the OxOpt model using Objectives 1 and 2, and Fig. 8.2 shows additional model results compared to the status quo scenario.

The model estimates that as of 2009, about US $6,000 per year was being spent on oxygen for childhood pneumonia in The Gambia, with this investment satisfying just over 45% of the total demand in the country (Fig. 8.2). Operating costs of about US $5,000 per year make up the majority of this expense. There are only five concentrators simulated in this scenario so the operating costs are largely (about 70%) due to cylinder costs (e.g., it is estimated that cylinder costs at Royal Victoria Hospital - serviced only by cylinders at the time - cost US $12,800 over five years). In total, the oxygen system in place in 2009 was delivering an estimated 0.85 million litres per year, fully treating about 500 patients and leaving 1860 untreated. Compared to having no oxygen at all, the model estimates that 34 lives were being saved over five years, at a cost per life saved of US $897.

Using Objective 1, satisfied demand improved to over 80% with an estimated total 5-year system cost of just under US $70,000 (Fig. 8.2). This solution consisted of 12 concentrators (one at each facility except Royal Victoria Hospital, which was allocated two), and backup battery systems at three facilities, Serekunda, Fajikunda and Bansang (Table 8.7), which also happen to have three of the highest patient admission rates. Limiting the available budget to US $60,000 (Objective 2) resulted in a solution with the same number of concentrators (i.e. 12) but two fewer alternative energy systems (at the Serekunda and Fajikunda health facilities) (Table 8.7), which resulted in less satisfied demand (~72%). For the solution proposed using Objective 1, about 18.2% of the 7.6 million L of oxygen supplied was generated while concentrators were being powered by alternative energy sources. In the case of Objective 2, just 7.2% of the 6.7 million L was supplied via an alternative energy system (not shown).
## Table 8.7: OxOpt model decision variable values for The Gambia national analysis using Objectives 1 and 2.

<table>
<thead>
<tr>
<th>Region</th>
<th>Name</th>
<th>Type</th>
<th>No. of concentrators, $C_i$</th>
<th>Alternative energy source (yes/no), $A_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower River</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Royal Victoria</td>
<td>Hospital</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Serekunda</td>
<td>Health Centre</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Fajikunda</td>
<td>Health Centre</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Brikama</td>
<td>Hospital</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Bwiam</td>
<td>Health Centre</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Essau</td>
<td>Hospital</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Farafenni</td>
<td>Health Centre</td>
<td>1</td>
<td>1</td>
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<tr>
<td></td>
<td>Soma</td>
<td>Health Centre</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Kuntaur</td>
<td>Hospital</td>
<td>1</td>
<td>1</td>
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<tr>
<td></td>
<td>Bansang</td>
<td>Hospital</td>
<td>1</td>
<td>1</td>
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<tr>
<td></td>
<td>Basse</td>
<td>Health Centre</td>
<td>1</td>
<td>0</td>
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<td></td>
<td>Upper River</td>
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</table>

**OBJ 1: Meet 80% of oxygen demand**

<table>
<thead>
<tr>
<th>Region</th>
<th>Name</th>
<th>Type</th>
<th>No. of concentrators, $C_i$</th>
<th>Alternative energy source (yes/no), $A_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower River</td>
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<td>Royal Victoria</td>
<td>Hospital</td>
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<td></td>
<td>Serekunda</td>
<td>Health Centre</td>
<td>1</td>
<td>1</td>
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<tr>
<td></td>
<td>Fajikunda</td>
<td>Health Centre</td>
<td>1</td>
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<tr>
<td></td>
<td>Brikama</td>
<td>Hospital</td>
<td>1</td>
<td>0</td>
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<tr>
<td></td>
<td>Bwiam</td>
<td>Health Centre</td>
<td>1</td>
<td>0</td>
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<tr>
<td></td>
<td>Essau</td>
<td>Hospital</td>
<td>1</td>
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<td>Farafenni</td>
<td>Health Centre</td>
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<td>Soma</td>
<td>Health Centre</td>
<td>1</td>
<td>0</td>
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<tr>
<td></td>
<td>Kuntaur</td>
<td>Hospital</td>
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<td></td>
<td>Bansang</td>
<td>Hospital</td>
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<td></td>
<td>Basse</td>
<td>Health Centre</td>
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<td>Upper River</td>
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</tbody>
</table>

**OBJ 2: Meet $60,000 target budget**

<table>
<thead>
<tr>
<th>Region</th>
<th>Name</th>
<th>Type</th>
<th>No. of concentrators, $C_i$</th>
<th>Alternative energy source (yes/no), $A_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower River</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Royal Victoria</td>
<td>Hospital</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Serekunda</td>
<td>Health Centre</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Fajikunda</td>
<td>Health Centre</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Brikama</td>
<td>Hospital</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Bwiam</td>
<td>Health Centre</td>
<td>1</td>
<td>0</td>
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<tr>
<td></td>
<td>Essau</td>
<td>Hospital</td>
<td>1</td>
<td>1</td>
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<tr>
<td></td>
<td>Farafenni</td>
<td>Health Centre</td>
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<td>Soma</td>
<td>Health Centre</td>
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<tr>
<td></td>
<td>Kuntaur</td>
<td>Hospital</td>
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<td></td>
<td>Bansang</td>
<td>Hospital</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Basse</td>
<td>Health Centre</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

**Figure 8.2: OxOpt model results for The Gambia comparing status quo (2009) scenario to national analyses using Objectives 1 and 2.**

Objective 1 minimized the cost to achieve at least 80% demand and Objective 2 minimized unsatisfied demand for a maximum 5-year cost of US $60,000. Mean ± standard deviation (SD) over 50 simulation iterations. DALY = disability adjusted life year. All costs in $USD.
Figure 8.3 compares the status quo and the two optimized national solutions across several cost-effectiveness measures. There is a positive linear relationship between the costs of these solutions (between US $30,000 and $70,000) and the percent of oxygen demand satisfied - i.e., it costs about US $1,000 per 1% increase in demand satisfied beyond the status quo level (Fig. 8.3A).\textsuperscript{3} In terms of lives saved, the Objective 2 solution was the most cost-effective solution, costing about US $883 per life saved versus Objective 1 at US $919 (Fig. 8.3B). Absolute number of lives saved increased by 121% and 94% using Objective 1 and 2, respectively, compared to the status quo. Objective 1 was slightly more cost-effective when considering total number of patients treated, at about US $50 per patient treated compared to US $53 for Objective 2 (Fig. 8.3C). Percent increase in patients treated compared to status quo was even more pronounced than number of lives saved, at 174% and 117% for Objectives 1 and 2, respectively. Despite poor performance in terms of total demand coverage, lives saved and patients treated, the status quo scenario was still the most efficient in terms of cost per 1000 L delivered (Fig. 8.3D). This shows the importance of evaluating oxygen systems based on health outcomes in addition to more technical measures of efficiency.

Figure 8.3: Cost-effectiveness results for The Gambia comparing status quo (2009) scenario to national analyses using Objective 1 and 2. Cost-effectiveness measures include: (A) Total 5-year system cost (capital cost and operating costs over 5 years) vs. percent of total oxygen demand satisfied; (B) Cost per life saved vs. total number of lives saved; (C) Cost per patient treated vs total number of patients treated; (D) Cost per 1000L oxygen delivered to patients vs. total L oxygen delivered. Standard deviations provided in Fig. 8.2. All costs in $USD.

Figure 8.4 shows a more detailed breakdown of the capital and operating costs for all three scenarios. In Case 1, capital equipment expenses are shown to be incurred in the first year, with estimates for annual operating costs thereafter. In Case 2, capital costs are amortized over an expected equipment lifespan of five years to give a better sense of the average annual cost to implement each recommendation.

\textsuperscript{3}This relationship does not hold true at higher percentages, as will be shown in section 8.5.2
This lifespan estimate is believed to be conservative given there is evidence of concentrators operating for greater than five years in The Gambia [18]. Long-term experience with battery backup systems beyond five years, however, is limited.

Figure 8.4: Financial results for The Gambia comparing status quo (2009) scenario to national analyses using Objective 1 and 2. Breakdown of annual capital and operating costs when capital costs are incurred in year 1 (Case 1) and when capital costs are amortized over equipment lifespan (5 years) (Case 2) for: (A) Status quo (2009) scenario; (B) Objective 1: minimize cost to satisfy 80% demand; (C) Objective 2: minimize unmet demand for maximum cost of US$60,000. All costs in $USD.

The capital cost in the status quo scenario (Fig. 8.4 A) is markedly less than the two optimized model recommendations (Figs. 8.4 B and C), however annual operating costs are comparable at about US $5,000 per year for the status quo versus about US $4,200 for the Objective 1 and 2 solutions (Fig. 8.4 - Case 1). Looking at Case 2, capital costs for Objective 1 and 2 solutions make up the majority of annual costs (about 64% to 69%). In summary, with a substantial initial capital outlay for better technology, health outcomes can be significantly improved with a comparable annual operating budget to what is currently being spent.

The OxOpt model places huge importance on supporting training, both at the initiation of an oxygen improvement project and as an on-going requirement for effective long-term maintenance and operation of the equipment (see section 3.3 for more details). Whereas the status quo scenario does not factor in any resources for training, about 33% and 40% of the total 5-year cost for the Objective 1 and 2 solutions, respectively, is dedicated to training. In fact, training makes up the majority of the annual operating costs in both optimized scenarios (about 52% in both cases). Without these funds allocated
for training, annual operating expenses are actually closer to US $2,000 per year - or about 40% of the status quo operating costs.

The other substantial operating cost is the cost of electricity. Just over 37% of the annual operating costs for both Objective 1 and 2 solutions are electricity costs. In section 8.5.5, a ‘what if’ scenario exploring the trade off in price of electricity versus the cost of off-grid solutions is explored in more detail.

Maintenance makes up the smallest proportion of operating costs (roughly 10% for both Objectives 1 and 2). As shown by the study presented in Chapter 3, maintenance costs for concentrators are minimal, provided there are trained technicians available to complete the repairs and perform preventive maintenance (hence the resources allocated for training described above) and spare parts are available. Although a small proportion of overall costs, it is still essential that this 10% is budgeted for to ensure the longevity of equipment. As discussed by La Vincente et al. [73] and Enarson et al. [42], when these resources are not budgeted for, concentrators can easily fall into disrepair.

8.5.2 Equity analysis

Introduction and scenario setup

The three scenarios of the national analysis in section 8.5.1 (i.e., status quo and optimized nation-wide solutions using Objective 1 and 2) provide a basis from which to explore the concept of equity in resource allocation and health outcomes. Specifically, we can look at the differences between hospitals and health centres, which loosely corresponds to the separation between urban/peri-urban centres and rural areas in The Gambia - i.e., a geographical perspective on health care equity (Fig. 8.5).

In the status quo scenario, unmet oxygen demand and resulting patient treatment coverage are highly inequitably distributed across hospitals and major health centres. For example, despite the fact that unmet demand is estimated to be 55% nationally (Fig. 8.2), hospitals face a shortage of about 36.5% whereas health centres face a shortage of 84.3%, largely due to the fact that four out of six health centres had no supply at all (Fig. 8.5). In hospitals, about 64% of pneumonia patients are either fully or partially treated, compared to just 16% in health centres.

When applying the OxOpt model to the country as a whole, the optimized scenarios improve this situation substantially, however there are still inequities observed. For example, in the case of Objective 1, despite overall demand satisfaction being greater than 80% as specified (Fig. 8.2), when grouped by health facility type, oxygen demand at hospitals is about 88% satisfied whereas demand at health centres is only 71% satisfied (Fig. 8.5). The amount of unsatisfied demand varies widely on a health facility-basis, ranging from about 2% at the main referral Royal Victoria Hospital to 56% at the Bwiam hospital (not shown). Consequently, patient treatment coverage is also not equitable; for example, the proportion of pneumonia patients that are fully or partially treated varies from about 60% to 99% across all facilities (not shown). In terms of resource allocation for the Objective 1 solution, with training costs excluded, about US $1,055 would be allocated per hospital per year but only US $650 per health centre per year.

The above example demonstrates a utilitarian approach to healthcare equity - maximizing overall benefit given limited resources. As such, perhaps the model-recommended resource allocation strategy is appropriate given that hospitals have higher patient volumes and tend to receive higher-risk patients. However, as was shown in the review paper of Chapter 2 and Appendix A, healthcare equity can be
**Figure 8.5:** Breakdown of results for status quo and national Objective 1 and 2 analyses by hospitals and health centres. Hospitals: Royal Victoria, Serekunda, Bwiam, AFPRC, and Bansang. Health centres: Fajikunda, Brikama, Essau, Soma, Kuntaur, and Basse. Mean ± standard deviation (SD) over 50 simulation iterations. All costs in $USD.

operationalized using many different ethical perspectives. The *OxOpt* model can be used to analyze the effects of applying different equity lenses to this resource allocation challenge. Four additional equity scenarios (ES) were run to demonstrate how different principles of equity can be integrated into the framing of the optimization problem, as follows:

- **ES 1: Minimum egalitarian scenario** - Provide a minimum amount of technology equally for all health facilities. Each facility is allocated one oxygen concentrator and no alternative energy source.

- **ES 2: 80% minimum demand threshold imposed separately for hospitals and for health centres** - Unsatisfied demand across all hospitals, collectively, and all health facilities, collectively, cannot exceed 20%.

- **ES 3: 90% minimum demand threshold imposed separately for hospitals and for health centres** - Unsatisfied demand across all hospitals, collectively, and all health facilities, collectively, cannot exceed 10%.

- **ES 4: Maximum scenario** - Provide each health facility with all the technology it likely needs such that no individual facility faces a shortage greater than 10%. The maximum number of concentrators is provided at each facility, which may not be equal for each facility as it is based on expected peak demand. Every health facility is also allocated an appropriate alternative energy source, which may not be equal for each facility, but is chosen appropriately for each context (see Options Analysis in section 8.3).

In the case of ES 1 and ES 4, the scenarios are simulated using the SIM component of the *OxOpt* model.
model only (results are averaged over 50 simulation iterations). For ES 2 and ES 3, the full sim-opt functionality is used with Objective 1 to determine optimized solutions.

Results

Decision variable values for all the equity scenarios are summarized in Table 8.8; values that differ from one solution to the next are shaded. Figure 8.6 shows cost-effectiveness comparisons for all four equity scenarios (with complete model results provided in Appendix Fig. E.1).

Table 8.8: *OxOpt* model decision variable values for The Gambia equity scenarios (ES). ES 1: minimum technology allocation, one concentrator per health facility; ES 2: optimized with demand threshold set to 80%; ES 3: optimized with demand threshold set to 90%; and ES 4: maximum technology allocation. Values that differ from one solution to the next are shaded.

<table>
<thead>
<tr>
<th>Region</th>
<th>ES 1: Min scenario - One concentrator each with no alternative energy source</th>
<th>ES 2: Meet 80% of oxygen demand</th>
<th>ES 3: Meet 90% of oxygen demand</th>
<th>ES 4: Max scenario - Max number of concentrators with alternative energy source everywhere</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region</td>
<td>HF i</td>
<td>Name</td>
<td>Type</td>
<td>Main referral hospital</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Banjul</td>
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<td></td>
</tr>
<tr>
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<td>2</td>
<td>Lower River</td>
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<tr>
<td></td>
<td>4</td>
<td>Total</td>
<td></td>
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</tbody>
</table>

Compared to the status quo, the minimum scenario of just one concentrator per health facility (ES 1), which is estimated to cost about US $50,000 over 5 years (64.5% more than the status quo), improves oxygen coverage from 45.3% to 65.6% overall (Fig. 8.6A). Equity in oxygen coverage is also improved; satisfied demand among health centres would be about 60% compared to just 16% for the status quo (Appendix Fig. E.1).

The model suggests that to satisfy at least 80% of the oxygen demand at hospitals and health centres, separately (ES 2), five alternative energy systems should be added, which increases the estimated 5-year cost to about US $77,000 (Table 8.8 and Fig. 8.6A). To increase coverage to 90% (ES 3), a mixture of additional concentrators and alternative energy systems at two urban hospitals (RVH and Serekunda) and four health centres (Fajikunda, Brikama, Kuntaur and Basse) would be required, at an additional 5-year cost of US $34,800. At this coverage level and beyond, the linear relationship between total
cost and percent satisfied demand no longer holds; incremental increases in demand coverage require significant additional financial investments in technology. For example, the total 5-year cost to go from 90% coverage to nearly 100% (ES 4) increases by almost 100% - from US $111,800 to $220,700, or about US $13,600 per percent increase (Fig. 8.6A). Equity in oxygen coverage levels was maximized in ES 4, with all health facilities expected to satisfy 97.5% of their oxygen needs or greater (Appendix Fig. E.1).

Figure 8.6: Cost-effectiveness results comparing status quo scenario to four equity scenarios. ES 1: minimum technology allocation, one concentrator per health facility; ES 2: optimized with demand threshold set to 80%; ES 3: optimized with demand threshold set to 90%; and ES 4: maximum technology allocation. Cost-effectiveness measures include: (A) Total 5-year system cost (capital cost and operating costs over 5 years) vs. percent of total oxygen demand satisfied; (B) Cost per life saved vs. total number of lives saved; (C) Cost per patient treated vs total number of patients treated; (D) Cost per 1000 L oxygen delivered to patients vs. total L oxygen delivered. Standard deviations provided in Appendix Fig. E.1.

In terms of cost per life saved, ES 1 is the most cost-effective at US $817/life saved (Fig. 8.6B). The ES 2 solution (US $892/life saved), which is less than 10% more costly than the status quo (US $897/life saved), is expected to save about 130% more lives over five years. When considering cost per patient
treated (Fig. 8.6C), the ES 2 solution is slightly more cost-effective than both the ES 1 and status scenarios, and is expected to treat 1.6 and 3.0 times more patients, respectively, over five years. Both in terms of cost per life saved and cost per patient treated, the E4 solution is significantly more expensive for the incremental gains in potential health outcomes. As was the case with the national analysis, the status quo is the most efficient in terms of cost per 1000 L (Fig. 8.6D).

For all the equity scenarios presented, as oxygen demand coverage increases, the proportion of total cost dedicated to capital expenses, including upfront user and technician training, increases (from 58% for ES 1 to 89% for ES 4) whereas operating costs are estimated to remain relatively similar (i.e., between US $4,000 and $5,000 per year) (Appendix Fig. E.1). In order to satisfy higher percentages of total demand, the solutions become much more technology-intensive, particularly with the addition of alternative energy systems.

Going back to the national analysis of section 8.5.1, Fig. 8.7 compares results from the Objective 1 national analysis (i.e., 80% demand satisfied, nationally) to the ES 2 solution, where 80% of demand is satisfied at hospitals and health centres separately. In order to achieve this more equitable balance in demand coverage, a significant additional investment (approximately US $8,100) is required in the form of two additional alternative energy systems at the Essau and Soma health centres (Table 8.8). The only other difference in the two solutions is there is one less concentrator at the Royal Victoria Hospital in the ES 2 solution. This means for the national scenario, it was cheaper to add a concentrator at RVH, which has relatively good electricity, in order to increase satisfied demand there (to almost 98%) and exceed the 80% threshold nationally, than it was to add an alternative energy source at a health centre elsewhere in order to increase oxygen coverage. With the ES 2 solution, the proportion of pneumonia patients that are fully or partially treated is 88% and 89% for hospitals and health centres, respectively, whereas for the national analysis, this difference was 91% and 80% (Fig. 8.7).

The results of these equity scenarios highlight that depending on the goal of the oxygen improvement initiative, the make-up of the recommended oxygen solution and the resulting impact on satisfied oxygen demand and health outcomes, may be dramatically different. In particular, setting a national priority of satisfying a minimum amount of oxygen demand may result in highly inequitable access to oxygen due to limited resources in certain locations. A solution which applies the same technology for all settings may be ‘equal’ in the allocation of resources, but may not be the most cost-effective way of reaching as many patients as possible. Ensuring that health facilities have a more equitable potential to meet the oxygen needs of the populations they serve may require focusing more resources in certain locations than others.
### 8.5.3 Sensitivity analysis: Case fatality rate

#### Introduction and analysis setup

All scenarios thus far have assumed that the CFRs $\rho_u$, $\rho_p$, and $\rho_t$ are 15%, 12.5%, and 10%, respectively as discussed in section 8.2.2. This assumption represents a 33% reduction in mortality, which is slightly conservative compared to the 35% reduction reported by Duke et al. [41] in PNG.

This section explores how sensitive OxOpt model estimates of number of lives saved are to different values of $\rho_t$, $\rho_p$, and $\rho_u$. Seven different combinations of $\rho_u$ (ranging from 10% to 20%) and $\rho_t$ (ranging from 8% to 12%) were chosen to represent CFR ranges found in the literature for The Gambia and other low-resource settings [9,25,43,45,65,67,71,75,96,114,132,136,140]. These combinations represent reductions in mortality between 20% and 60% as shown in Fig. 8.8. For the status quo scenario and all equity scenarios (ES 1 to 4) from section 8.5.2, the number of lives saved was recalculated for each combination of $\rho_u$ and $\rho_t$ (with $\rho_p$ always being the midpoint between these two).

#### Results

The number of lives saved is very sensitive to the CFR values chosen (Fig. 8.8B; for complete results with standard deviations see Appendix Fig. E.2). For example, estimates differ by six times for the most extreme combinations - i.e., a decrease in mortality rate from 10% to 8% versus 20% to 8%. Furthermore, the higher the starting CFR ($\rho_u$), the more lives that are estimated to be saved. For example, with a $\rho_u$ of 20% and $\rho_t$ of 12% (a 40% reduction in mortality risk), the estimate for lives saved is 14% more than if mortality was reduced from 15% to 8% (a 47% reduction in mortality risk). In relation to the chosen
default, estimates could be up to 60% less or up to 140% more depending on the CFR combination.

As discussed in section 8.2.2, there is limited evidence available for mortality risk without oxygen therapy in The Gambia, as most studies provided access to oxygen as part of the study protocol. CFRs are also likely to vary across health facilities but this was not accounted for in the calculations. The default combination of $\rho_u = 15\%$ and $\rho_t = 10\%$ is believed to be conservative compared to other settings [41, 75]. For all remaining analyses, these default values will continue to be used, however the plausible range of values for the estimate for lives saved should be considered when calculating cost per lives saved.

![Figure 8.8: Sensitivity analysis: Different case fatality rates (CFR) for treated and untreated patients.](image)

**(A)** Analysis setup: % reduction in case fatality rate for different combinations of $\rho_t$ (treated with oxygen) and $\rho_u$ (untreated). The default used in all scenarios is $\rho_u = 15\%$ and $\rho_t = 10\%$ (i.e., a 33\% reduction in mortality risk); (B) Number of lives saved recalculated for all combinations of $\rho_t$ and $\rho_u$ for the status quo scenario and all equity scenarios (ES 1 to 4) from section 8.5.2. Default condition is highlighted. Standard deviations provided in Appendix Fig. E.2.

### 8.5.4 ‘What If’ scenario: Climate change and increased disease burden

**Introduction and scenario setup**

The *OxOpt* model can be used to explore ‘what if’ scenarios related to extreme climate changes and the resulting effects this might have on human health as well as the resources needed to support growing oxygen demands on health systems. The WHO predicts that environmental changes brought on by unmitigated climate change will lead to significant increases in illness and death [89, 153]. Sub-Saharan Africa is estimated to bear the highest burden of health effects despite contributing very little to overall climate change [5].

The Gambia, being a coastal country near the equator, is already experiencing the effects of climate change. Mean annual temperature has increased by 1°C since 1960, and is projected to increase between 1 and 3°C by 2060. Models project mean precipitation over West Africa to increase during the rainy season as well [144]. The duration of rainy season, however, has been decreasing in The Gambia, with increasing variability in annual rainfall [144].

There is growing evidence of an association between increasing maximum temperature and increasing incidence and risk of death from acute respiratory infection in Africa [5, 90, 129, 131]. For example, Thompson *et al.* [131] estimated that about 38\% of the incidence of disease in children in South Africa
may be attributable to climatic factors (namely, temperature and rainfall), and predicted that a unit increase in temperature will produce a 1.3-fold increase in the incidence of the five most prevalent illnesses in children, with diarrhoea and respiratory infections being the most prevalent [131].

Although there are no studies linking changes in climate to disease burden in The Gambia, the World Bank projects that extremes in weather as a result of climate change will adversely affect the public health of Gambians in the future [144], especially due to illnesses that exhibit seasonal patterns, such as respiratory syncytial virus (RSV), which peaks during rainy season [25, 67, 138, 139]. Extremes in weather as a result of climate change can exacerbate the incidence of these acute respiratory illnesses, increasing demands on limited oxygen supplies.

The scenarios presented in this chapter thus far assume that current levels of patient admission rates and hypoxaemia prevalence, and the duration and intensity of rainy season, remain relatively constant for the time horizons simulated (although there is some inherent variability due to the stochastic nature of the Patient Arrival and O\textsubscript{2} Demand discrete-event simulation model - see Chapter 5 and section 7.2). Given changes in global weather patterns and the effects this is having on human health, it would be prudent to explore scenarios with an increased burden of childhood acute respiratory illness to better understand the robustness of model recommendations in accommodating increased demands on oxygen supply.

To demonstrate this, the simulation component of the OxOpt model is used to test how well the ES\textsubscript{2} technology solution of section 8.5.2 (consisting of 11 oxygen concentrators, one at each health facility, and five alternative energy systems, two at hospitals and three at health centres - see Table 8.8) is able to cope with more extreme patient admission scenarios as follows:

- **CC 1: Moderate climate change** - Annual pneumonia admission rates at each health facility (λ\textsubscript{i}) are increased by 25%, rainy season shortened to 3 months, proportion of patients in rainy season at each health facility (η\textsubscript{i}) is increased from 45% to 55%, and hypoxaemia prevalence (h\textsubscript{i}) is increased from 12% to 15%.

- **CC 2: Extreme climate change** - Annual pneumonia admission rates at each health facility (λ\textsubscript{i}) are increased by 50%, rainy season shortened to 3 months, proportion of patients in rainy season at each health facility (η\textsubscript{i}) is increased from 45% to 55%, and hypoxaemia prevalence (h\textsubscript{i}) is increased from 12% to 20%.

All other model inputs remain as stated in Table 8.5.

**Results**

Figure 8.9 shows the robustness of the model-recommended oxygen technology solution for equity scenario 2 against moderate and extreme climate change scenarios (complete model results are provided in Appendix Fig. E.3). As a result of additional and more concentrated patient admissions in the high season, the model predicts that median peak concurrent oxygen demand (L/min) across all health facilities would increase from 4.1 L/min [IQR: 3.3, 5.3] to 5.5 L/min [IQR: 4.2, 7.4] and 6.8 L/min [IQR: 5.1, 9.8] for the moderate (CC1) and extreme (CC2) climate scenarios, respectively (Fig. 8.9A). The volume of unsatisfied demand also increases, especially as concurrent demand exceeds 5 L/min, which is the maximum that one concentrator can supply. Despite these increases in unsatisfied demand, the system is still expected to supply over 80% of total oxygen need (Fig. 8.9B), even under the extreme...
condition of 50% more patient admissions (CC2), and this holds true for hospitals and health centres separately (Appendix Fig. E.3).

The capital equipment cost is constant, but annual operating costs would increase by 10.7% and 26.8% for the moderate and extreme climate change scenarios, respectively, due to higher concentrator usage and thus additional electricity (kWh) costs (Fig 8.9B).

Figure 8.9: Model results for ES 2 solution under moderate and extreme climate change conditions. ES 2: optimized solution that meets a minimum of 80% oxygen demand. For climate change scenarios, annual patient admission rates are increased by 25% (CC1) and 50% (CC 2) compared to baseline across all health facilities. Model outputs compared are: (A) Volume of unsatisfied demand (L) vs median peak concurrent demand (L/min); (B) Total 5-year operating cost (capital costs are fixed in this analysis) vs. percent of total oxygen demand satisfied; (C) Cost per patient treated vs. total number of patients treated; (D) Cost per life saved vs. total number of lives saved. Standard deviations provided in Appendix Fig. E.3.

In terms of cost-effectiveness measures, the cost per patient treated and cost per life saved improve
considerably for the two climate change scenarios (Figs. 8.9 C and D). This is because by including a 5-way flowmeter device with each oxygen concentrator, one 5 L/min concentrator can support oxygen therapy for up to five children at flow rates of 1 L/min or a maximum of two children at 2 L/min. The concentrator will consume the same amount of energy whether it is supplying 1 or 5 children with oxygen, thus the addition of concurrent patients does not increase operating costs.

These results highlight how the OxOpt-recommended solution for meeting 80% of The Gambia’s oxygen needs would be resilient to increases in patient admissions due to climate change, in terms of the amount of oxygen demand satisfied, the minimal additional operating costs required, and the overall cost-effectiveness of the solution in treating patients and saving lives.

8.5.5 ‘What If’ scenario: Changes in technology and innovation

Introduction and scenario setup

All of the scenarios presented thus far have assumed an equipment lifespan of five years. This is likely conservative for The Gambia, where it was shown that median age of concentrators was over six years [18], with many devices still in service after eight years of operation [21]. With effective training and maintenance, and equipment selection based on evidence and quality [102, 103, 152], it is worthwhile exploring how the long-term cost-effectiveness of concentrator-based systems improves with equipment longevity.

In addition, as was shown in the review paper of Appendix A, one area of global health that OR can make a unique contribution to is the analysis of health innovations that are still in development or proof of concept stages [20]. OR can help highlight important design criteria or targets for the development of such new innovations, in terms of both cost and minimum levels of efficacy or specificity required to achieve desired outcomes. In the case of medical oxygen supply, there has been a recent focus on solar-powered oxygen concentrators as a potential solution to oxygen scarcity in sub-Saharan Africa, where sun is abundant [133]. Other innovations, for example, an electricity-free oxygen concentrator [122], are also being developed and piloted to address poor electricity supply, but are in an early proof-of-concept stage. In situations where there is no grid supply at all, such innovations may be the only option, but where there is some electricity, the cost-effectiveness of such systems would need to be compared to the best available grid-tied systems. Due to high electricity rates in The Gambia, and the country’s vulnerability to increasing oil prices, electricity-free options might become cost-effective in the future.

To explore how equipment lifespan impacts the cost-effectiveness of concentrators, and the tradeoffs between grid-tied systems (given current $ per kWh and potential increases in $ per kWh) compared to off-grid innovations, the following scenarios are explored for the case of The Gambia:

- **TECH 1: Equipment lifespans** - Simulate an OxOpt-recommended solution for equipment lifespans of 6, 8 and 10 years to demonstrate how cost-effectiveness improves the longer equipment remains in-service

- **TECH 2: Grid-tied vs off-grid solutions** - For two example health facilities (Royal Victoria hospital and Basse health centre) determine:

  2a) At what cost would a solar-powered concentrator (or electricity-free concentrator) system be more cost-effective than an optimized grid-charged battery-backup or UPS system given the current cost per kWh of grid power?
2b) Should energy costs rise in the future, at what $ per kWh would a solar-powered concentrator (or electricity-free concentrator) be more cost-effective than an optimized grid-charged battery-backup or UPS system given the best available cost estimate for off-grid systems?

The Royal Victoria hospital is the main referral hospital in the capital city and has relatively good electricity supply (~99%), and Basse health centre is a rural facility in the most interior village in The Gambia with electricity for about 20 hours a day. Both facilities require alternative energy sources if they aim to meet 100% of their oxygen needs, and could stand to gain from not having to pay high rates per kWh due to their high grid-usage if other options were available.

Results

Using the OxOpt-recommended solution for equity scenario 2 (ES 2) as an example, Fig. 8.10A shows how the cost per year decreases with increasing equipment lifespan. The original optimized solution for ES 2 used a default lifespan of five years (see ES 2, Table 8.8 and Fig. 8.6) and was estimated to cost about US $77,000 over five years; US $56,200 in equipment and initial training costs, with annual operating costs of US $4,150. Regardless of equipment lifespan, annual operating costs should remain relatively constant; thus if equipment lifespan doubles from five to 10 years, the cost per year (with capital costs amortized over the equipment lifespan) decreases by about 36%, from US $15,400 to $9,800. Other cost-effectiveness measures also become more favourable as equipment lifespan increases, for example, the cost per life saved (Fig. 8.10B), cost per patient treated and cost per 1000L oxygen delivered all decrease by 35 to 36% as lifespans reach 10 years.

Figure 8.10: TECH 1: Cost per year and cost per life saved of oxygen system meeting 80% of Gambia’s oxygen needs (ES 2) for increasing equipment lifespans. (A) Cost per year is the capital cost amortized over equipment lifespan plus annual operating cost. (B) Cost per life saved is total system cost divided by estimated number of lives saved over equipment lifespan. Lifespan of 5 years was the default used when ES 2 was originally optimized (see Table 8.8 and Fig. 8.6).

Figure 8.11 plots total 5-year cost of different previously computed technology solutions (i.e., ES 1, ES 3 and ES 4) meeting at least 75% of the oxygen needs for the Royal Victoria hospital and Basse health centre. The figure indicates that for a target threshold of 95% of demand satisfied, an off-grid
solar or electricity-free oxygen system would have to cost less than about US $6,500 and US $11,500 for RVH and Basse, respectively. These cost targets would be the 5-year total cost to operate at least two oxygen concentrators, assuming a 5-year equipment lifespan, with operating costs included. Given that the two known solar-powered systems piloted in Africa reported costs of US $13,000 (in 2001) [118] and US $18,000 (in 2013) [133] to power one concentrator, it seems unlikely that solar will be a cost-effective option for these two health facilities in the near future.

Figure 8.12 shows how vulnerable the Royal Victoria and Basse health facilities are to increasing energy costs. For example, the total 5-year system cost to meet 98% of the oxygen demand at RVH is expected to increase 11.2%, 22.3% and 44.6% if electricity prices were to increase 1.5, 2 and 3 times, respectively. Basse, which consumes about one sixth of the energy that RVH does to treat pneumonia patients, would be much less affected by energy price increases, with total system cost to satisfy 98% of demand expected to increase by only 5% if energy prices tripled.

In the RVH case, a solar-powered oxygen system costing US $13,000 over 5 years would be cost-effective if the demand target was 98% or above and electricity rates doubled or tripled. In other words, RVH could satisfy 99.7% of its oxygen needs using the model-recommended combination of concentrators and UPS for less than the estimated cost of solar if energy prices remained below 1.5 times the current rate. For Basse, a solar-powered system is cost-effective if the target demand satisfaction rate is above about 97%, irregardless of energy price increases. Otherwise, the combination of oxygen concentrators and a battery backup system is the cheaper option.

Figure 8.11: TECH 2a: Total 5-year cost for the Royal Victoria Hospital and Basse Health Centre for different thresholds of satisfied demand indicating target price points for off-grid solutions. Consecutive data points are for previously computed ES 1, ES 3 and ES 4 solutions. Training costs excluded from total. Target price point for off-grid solar or electricity-free oxygen system indicated for 95% demand threshold (assuming same equipment lifespan).
8.5.6 Summary of OxOpt Solutions and Recommendations for The Gambia

In a real-world application, decisions about oxygen technology allocation in The Gambia would not be based solely on the scenarios presented in this case study. The OxOpt model is intended to be used in collaboration with administrators or decision makers in ministries of health who would be involved with choosing which scenarios and analyses would be most useful to them. That being said, the results presented herein can be interpreted to provide recommendations for how The Gambia might strategically improve their oxygen supply situation.

Figure 8.13 summarizes the number of lives saved versus cost for all of the OxOpt national-level (OBJ1 and OBJ2) and equity (ES1 to ES4) solutions from this case study. While all solutions are more costly than the status quo on a 5-year total cost basis (Fig. 8.13A), the ES1 and OBJ2 solutions are more cost-effective in terms of cost per life saved, and would be expected to save between 1.8 and 1.9 times as many lives as the status quo (Fig. 8.13B).

Based on these results, as a minimum first step, it is recommended that The Gambia implement the ES1 solution - i.e., provide each facility with one oxygen concentrator. Not only is this solution an important step towards a more equitable allocation of resources, it is the most cost-effective in terms of cost per life saved. Resources that were originally paying for cylinder oxygen (∼$21,300 over five years) can be reallocated to support the purchase (including training) of five concentrators to be placed at facilities that were previously without, while the existing five concentrators remain where they are. Minimal additional funds (∼$19,500 over five years, or $3,900/yr) would be required to provide the remaining facility with one concentrator.

This recommendation could be implemented in a stepwise fashion, where new facilities are provided with concentrators based on patient admissions, starting with the Royal Victoria Hospital which sees about 650 patients per year down to Kuntaur which treats about 80 patients per year (see Table 8.5).
Next, The Gambia should work towards achieving solution ES2, which would involve the installation of five backup battery systems to provide continuity of power to existing concentrators, at Serekunda, Fajikunda, Essau, Soma, Bansang health facilities. This solution improves overall satisfied demand from about 66% to over 85% and is expected to save an additional 3 lives per year. The OBJ1 and OBJ2 solutions can be interim steps towards this goal. They are not as equitable between urban and rural areas as ES2, but are more cost-effective in terms of cost per life saved (Fig. 8.13B). These solutions indicate that Serekunda, Fajikunda and Bansang should be prioritized for battery systems (Table 8.7), followed by Soma and Essau.

As shown in Fig. 8.13A, beyond the ES2 solution, considerable additional financial investment is needed to achieve minor gains in expected lives saved. The Gambia would have to consider budgetary limitations and other competing child health interventions that need funding to determine whether it is feasible to dedicate the necessary funds to achieve greater than 90% oxygen demand coverage.

Figure 8.13: Lives saved vs (A) total system cost and (B) cost per life saved for all analyzed OxOpt solutions. OBJ1: optimized solution to satisfy 80% of oxygen demand, nationally; OBJ2: optimized solution for a restricted budget of $60,000; ES1: equity solution whereby all health facilities are given one concentrator; ES2 and ES 3: equity solutions whereby 80% and 90% of demand, respectively, is satisfied for hospitals and health facilities, separately; and ES4: equity solution whereby all facilities are provided with all expected technology needs.

8.6 Discussion for The Gambia Case Study

The OxOpt model recommendations for various 5-year scenarios have the potential to save about 61 to 93 lives, or 12 to 19 lives per year, representing about 8.4% to 12.8% of annual in-hospital pneumonia deaths in the country [96, 110]. The 5-year total costs of these solutions range from about US $50,000 to US $220,700 depending on the level of total oxygen demand satisfied and whether these thresholds are applied equitably to both hospitals and health centres, alike.

These results highlight the value of using an optimization approach to oxygen technology planning, as several solutions resulted in more efficient use of limited resources compared to the status quo situation. For example, the ES 1 solution was 9% more cost-effective in terms of $/life saved, and was projected to save almost double the amount of lives. The ES 2 solution, which is expected to deliver twice as many
L of oxygen per year as the status quo, is projected to treat almost three times as many patients.

The various OxOpt solutions include low numbers of concentrators (max 3) at each health facility and UPS or battery backup systems for continuity of electricity supply. In order to cover more and more of the oxygen needs of health facilities, the solutions become more capital intensive (i.e., the relationship between cost and oxygen demand coverage is not linear). The model helps quantify this phenomenon of diminishing health returns, which is a very real dilemma for health administrators when resources are limited.

Model results also showed that optimizing technology and resource allocation based on national demand coverage targets may lead to wide inequities across health facilities in terms of patients treated and lives saved. By applying different equity lenses to OxOpt objectives (e.g., all facilities shall receive equal resources, satisfied demand must be equal for hospitals and health centres, etc.), one can easily explore the trade-offs and consequences of these different perspectives.

These results also highlight that due to capital equipment costs making up the majority of oxygen system costs, the annual cost to operate such systems is highly dependent on equipment lifespan. The scenarios presented herein conservatively apply a lifespan of five years, however evidence has shown concentrators to be in operation in The Gambia for up to eight years [18,21], which would improve the cost per life saved by nearly 30%. If the systems are well maintained, and lifespan of the equipment increases, the economics become even more favourable.

Despite the current high electricity rates in The Gambia, grid-tied systems may still be more cost-effective than off-grid or electricity-free oxygen delivery systems for most Gambian health facilities given the high initial capital costs of such technologies and the fact that these health facilities typically have electricity for at least 12 hours per day. Nevertheless, this analysis has highlighted target price points at which such technologies will become cost-effective in The Gambia, which may be feasibly reached as the cost of photovoltaic continues to decrease [123], and product design and development of electricity-free oxygen generation is optimized [122]. This analysis does not negate the fact that solar-powered or electricity-free oxygen concentrators may be the only option in settings with no grid connectivity.

It was also demonstrated that the oxygen systems recommended by the model to meet current patient demands would be quite resilient to increased disease burden due to climate change or other external factors. This is because with the inclusion of appropriate flow-splitting technology, oxygen concentrators, which normally support adults, can supply oxygen to multiple children at once, immediately increasing the efficient use of oxygen generated. Health facilities that typically require oxygen for one or two patients simultaneously could support double or triple the number of children without additional equipment.

Although the OxOpt tool is intended to be used in collaboration with administrators or decision makers at the Ministry of Health, a recommended strategy for The Gambia was provided based on the scenarios presented. Since The Gambia is fully aware of the health inequities that exist between their urban and rural regions [50], the recommendation aims to balance cost-effectiveness with a more equitable geographic allocation of resources. First, the inefficient use of funds on cylinders is reallocated to provide concentrators in locations that previously had no supply. Then, in a staged approach, alternative energy technologies would be introduced incrementally in a prioritized manner based on need, with the ultimate goal of achieving the ES2 solution or better (ES3 or ES4).

The national solutions (OBJ1 and OBJ2) are slightly more cost-effective than the proposed recommendation, however they would likely only exacerbate the inequities in child mortality The Gambia is already facing between urban and rural regions, due to their disproportionate allocation of resources.
The case study did not include a scenario representing no increase in spending. While such a scenario is worthwhile exploring in theory, adoption of such a solution in practice could have major moral implications. For example, if the model suggested that the optimal use of existing concentrators required relocating several of them to different health facilities, could the ministry of health remove the only oxygen source from certain locations that were previously treating patients? To avoid such ethical dilemmas, the recommended strategy focuses on getting at least one concentrator in every facility as a first step.

The results for all the scenarios presented are very specific to the case of The Gambia, but can be compared to other projects in the literature. For example, the cost-effectiveness of the various different OxOpt solutions (ranging from US $49.90 to US $119.30 per child treated and US $817 to US $2,384 per life saved) are comparable to the improved oxygen program introduced by Duke et al. [41] in PNG, which was estimated to cost US $51 per child treated and US $1,673 per life saved. In this case, however, the five hospitals chosen had suitable mains power and most also had back-up generators [86], so they did not need to include alternative energy options for poor electricity supply. Their estimates also did not include the additional cost of electricity to run the concentrators [41], which was a cost accounted for in the OxOpt model. It is difficult to make direct comparisons, however, as this study only followed patients across 5 hospitals for 27 months post-oxygen intervention.

The costs per child treated for various OxOpt model recommendations are also favourable compared to other child health interventions, such as oral rehydration solution (US $75 per child) and antibiotic treatment for pneumonia (US $150 per child), as evidenced by studies in other parts of the world (southeast Asia and sub-Saharan Africa) [127]. Even the most expensive solution (ES 4), with an estimated cost per life saved of US $2,384, compares favourably to other interventions to reduce deaths from pneumonia, including pneumococcal conjugate vaccines (estimated US $4,500 per life saved) [121].

These cost-effectiveness results are sensitive to model estimates for number of lives saved, which is highly dependent on the case fatality rates (and resulting reduction in mortality risk) used. However, the assumptions made for mortality reduction due to access to oxygen for The Gambia are arguably quite conservative compared to results from other countries [41, 75], meaning the solutions proposed would likely be even more cost-effective than reported here.
8.6.1 Limitations

There are certain limitations acknowledged for this case study. First, for simplicity, the same case fatality rates ($\rho_t$, $\rho_p$, and $\rho_u$) and hypoxaemia prevalence ($h_i$) were used for all health facilities. Different studies in The Gambia [25, 67, 71, 96, 114, 136, 140] and elsewhere [41], suggest it is possible that these could differ across health facilities within a country. The model also assumes hypoxaemia prevalence and mortality rate are constant throughout the year. There is limited evidence to suggest that hypoxaemia prevalence [67] and mortality rate in childhood illnesses [25] are higher in the rainy season. The scenarios presented in this chapter do not go into this level of detail for each health facility. Sensitivity to hypoxaemia prevalence and proportion of patients in high season was demonstrated in Chapter 5.

Second, the analysis was also restricted to pneumonia, which underestimates total paediatric oxygen needs due to other severe illnesses that results in hypoxaemia and thus clinical need for oxygen (e.g., severe malaria, sepsis). Furthermore, there are other clinical uses of oxygen beyond the treatment of hypoxaemia (e.g., anaesthesia, bubble CPAP, and nebulizers) [152] that are not considered by the model. Nevertheless, the analysis as presented allows for the budgeting of targeted funds towards tackling the leading cause of death in children, and allows for a direct comparison of cost-effectiveness to other oxygen programs and other interventions for childhood diseases.

Last, the model does not include resources for pulse oximetry, which should be used in conjunction with oxygen concentrators to identify hypoxaemic patients and monitor oxygen therapy [152]. There is much less evidence for the use of pulse oximetry in low-resource settings compared to oxygen concentrators so data on this technology could not be incorporated into the model with as much confidence; however, as more is known about the use, maintenance, and costs of these important devices, this could easily be incorporated into the OxOpt model.
Chapter 9

Conclusion

9.1 Summary of Thesis Contributions

This thesis presents several significant contributions to the challenge of supplying medical oxygen in low-resource settings.

On the supply-side, to address the lack of evidence of the long term reliability of oxygen concentrators in low-resource settings, this thesis contributes the first-ever longitudinal analysis of oxygen concentrator maintenance histories. This analysis highlighted the importance of an equipment support ecosystem including resources for spare parts and training, and demonstrated that a skills-based approach to training could manage 90% of concentrator failures, leading to longer lifespans for these devices. In addition, an in-depth analysis of alternative energy systems provides the foundation for a decision-tree to guide the appropriate choice of energy source given varying levels of grid availability and system costs. These analyses were informed by field experience in The Gambia, which included first-hand observations of the challenges of oxygen provision in health facilities, and experience implementing and evaluating UPS and battery backup systems.

To address the demand-side challenge of scarce data on local oxygen needs in low-resource health facilities, a discrete-event simulation model was developed to estimate demand for oxygen based on five key factors: annual pneumonia admission rate, hypoxaemia prevalence, degree of seasonality, treatment duration, and oxygen flow rate. A theoretical analysis using the model demonstrated that oxygen systems tailored to meet average demand levels can severely underestimate the oxygen needs of a health facility during seasonal highs as well as random peaks throughout the year, leaving many patients under-served or even untreated altogether.

To address the lack of analytical approaches to oxygen technology planning that take the complexities of supply and demand into account, a novel simulation-optimization model – the OxOpt model – was developed. The model identifies the optimal combination of technologies that will meet oxygen needs across several health facilities.

The model was designed to be flexible and meet the needs of different decision-makers. Because the model is built on-the-fly with modular components, it is highly scalable and can be applied to one facility, several facilities in a region or district, or across an entire health system. There is also flexibility in how the optimization objective function is framed; the problem can minimize total system cost or minimize unsatisfied oxygen need, subject to constraints on target demand coverage and budget. The simulation
component can also be used independently of the optimization component, allowing users to compute all the output metrics offered by the OxOpt model for a specific prescribed situation. This flexibility allows decision-makers to run innumerable scenarios exploring tradeoffs in cost versus satisfied oxygen demand, as well as other ‘what-if’ scenarios exploring changes in future demand, costs, and technological advancements.

The case study of The Gambia demonstrated how the OxOpt model would be used within a Health Needs Assessment framework. Specific model inputs were informed by a review of literature, empirical measurement of electricity availability at individual health facilities, and real-world costing data for The Gambia, all of which are useful contributions in and of themselves towards a better understanding of the challenges of oxygen supply and demand in low-resource settings. This case study also showed how the OxOpt model can be used to analyze the oxygen problem through different equity lenses and to explore different ‘what if’ scenarios that are relevant to a specific context.

More broadly, this thesis has demonstrated that operations research is well-suited to analyze the oxygen supply and demand problem, and addresses an identified gap in the literature on the use of OR for medical technology planning in low-income countries. There is a huge opportunity to continue to apply OR to global health challenges related to medical technologies in low-resource settings.

Elements of this research are already having a meaningful impact. For example, two components of this research have been cited in the WHO’s Technical Specifications for Oxygen Concentrators [152], a document “intended to serve as a resource for the planning and provision of local and national oxygen concentrator systems for use by administrators, clinicians and technicians who are interested in improving access to oxygen therapy and reducing global mortality associated with hypoxaemia” [152]. First, the battery backup system described in Chapter 4 and [17,22] is referenced as an example of how to provide back-up power in settings with poor power. Second, the work on oxygen concentrator maintenance in Chapter 3 [18] is cited as a source of guidance on the useful lifespan of concentrators, and on planning and budgeting for spare parts and repairs. The work of Chapter 3 was also cited in a recent Textbook of Global Health (ed. Birn et al., 2017) [12] as an example of a collaborative effort towards providing equipment and technology in a low-resource setting that considers training and maintenance - important building blocks of health care systems.

9.2 Future Work

The most immediate extension to this thesis will be to apply the OxOpt model to a real-world setting. This will involve finding appropriate and willing partners in a country wanting to improve their oxygen supply, conducting a situational analysis to collect relevant model inputs, running scenarios to suit the needs of decision-makers, and developing a plan to implement model recommendations.

The OxOpt model could also be expanded to include additional features. For the health facility-level simulation, other illnesses could be incorporated to estimate oxygen demands across a wider range of applications within a health facility. This would involve incorporating separate input streams of patients into the discrete-event simulation model, with arrival patterns appropriate for those illnesses, and combining them with the pneumonia patients. In addition, the model currently treats all under 5 admissions alike; future work could involve distinguishing between neonatal admissions and children 12 to 59 months of age, as there is some evidence supporting different levels of hypoxaemia and different case fatality rates for these two patient groups [67,152]. Similarly, this would involve creating separate
input streams for neonatal and older children, and assigning different patient characteristics to them (e.g., hypoxaemia prevalence, flow rate distribution, treatment duration distribution, etc.) when they are admitted to a health facility.

On the optimization side, future work could involve exploring ways to improve the efficiency of model processing. For the scenarios presented throughout this thesis, processing time ranged from a couple of hours to a few days, depending on how many health facilities were being modelled at a time.

Additional sensitivity analyses for various model inputs could also be the subject of future work. With over 25 different inputs to the model, it was not possible to analyze model outcomes for all possible ranges of all inputs.

More broadly, the operations research principles applied in the OxOpt model could easily be applied to the analysis of other non-concentrator-based solutions that are emerging for the provision of oxygen in low-resource settings. For example, the Hewa Tele program in Kenya, a public-private-partnership between the GE Foundation, the Ministry of Health, the Centre for Public Health and Development, and others, which uses a hub-and-spoke cylinder-based approach whereby cylinders are filled at a central plant and delivered to hospitals based on need. By owning and operating the entire supply chain, and taking away the monopoly that the private sector had on oxygen supply, the vision is to be able to supply a cheaper, more reliable source of oxygen for the public health system. OR could easily be applied to the analysis of such a distribution model, in particular discrete-event simulation, which is well-suited to problems of systems operations and supply logistics. It was beyond the scope of this thesis to compare the concentrator-based solutions recommended by OxOpt with such a fundamentally different supply model.

Outside of the modeling work, there is potential to expand upon other elements of this thesis. For example, referring to the work on concentrator maintenance of Chapter 3, the WHO’s Technical Specifications document stated “more studies such as this are needed to demonstrate the cost-effectiveness and simplicity of oxygen concentrator-based systems” [152]. As the field-testing of oxygen solutions involving alternative energy systems continues, future work could involve evaluating the performance of these systems over time, such that even more evidence can be incorporated into the OxOpt model on the longevity of batteries, panels, etc., improving cost estimates and resource allocation towards maintenance and training. In addition, the proposed oxygen concentrator training curriculum for biomedical engineering technicians in low-resource settings, arising from the work of Chapter 3, could be field tested for effectiveness in addressing the maintenance needs of concentrators in low-resource settings.
Bibliography


Appendix A

Operations Research in Global Health: A Scoping Review with a Focus on the Themes of Health Equity and Impact

This work was previously published in the open access journal Health Research Policy and Systems (full citation: Bradley, B. D., et al. (2017) Operations research in global health: a scoping review with a focus on the themes of health equity and impact. Health Research Policy and Systems. 15:32. [20]). The publisher’s version has been reproduced here under the Creative Commons Attribution (CC BY) license.
Operations research in global health: a scoping review with a focus on the themes of health equity and impact

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Abstract

Background: Operations research (OR) is a discipline that uses advanced analytical methods (e.g. simulation, optimisation, decision analysis) to better understand complex systems and aid in decision-making.

Summary: Herein, we present a scoping review of the use of OR to analyse issues in global health, with an emphasis on health equity and research impact. A systematic search of five databases was designed to identify relevant published literature. A global overview of 1099 studies highlights the geographic distribution of OR and common OR methods used. From this collection of literature, a narrative description of the use of OR across four main application areas of global health – health systems and operations, clinical medicine, public health and health innovation – is also presented. The theme of health equity is then explored in detail through a subset of 44 studies. Health equity is a critical element of global health that cuts across all four application areas, and is an issue particularly amenable to analysis through OR. Finally, we present seven select cases of OR analyses that have been implemented or have influenced decision-making in global health policy or practice. Based on these cases, we identify three key drivers for success in bridging the gap between OR and global health policy, namely international collaboration with stakeholders, use of contextually appropriate data, and varied communication outlets for research findings. Such cases, however, represent a very small proportion of the literature found.

Conclusion: Poor availability of representative and quality data, and a lack of collaboration between those who develop OR models and stakeholders in the contexts where OR analyses are intended to serve, were found to be common challenges for effective OR modelling in global health.

Keywords: Operations research, Modelling, Policy, Decision-making, Global health, Health systems, Health equity, Developing countries, Low-resource settings

Background

‘Global health’ broadly refers to “an area for study, research, and practice that places a priority on improving health and achieving equity in health for all people worldwide” [1]. From population-based prevention to individual-level clinical care, global health encompasses health issues and solutions that transcend borders, and involves a collaborative and interdisciplinary effort [1]. The goal of achieving equity in health, namely the absence of systematic disparities in health or in the major social determinants of health between groups with different levels of underlying social advantage/disadvantage [2], has become a particularly important part of the post-2015 development agenda [3–6]. Globally, major progress has been made towards certain Millennium Development Goals and targets; however, many low- and middle-income countries (LMICs), especially in sub-Saharan Africa and Asia, continue to experience high health inequities, both within and between countries [3, 4]. Further, these countries carry most of the world’s burden of morbidity and mortality; for example, more than 99% of under-5 child deaths in 2010 occurred in...
LMICs, and although mortality rates fell in most monitored countries, 15 countries experienced increases in the absolute number of deaths, with 12 of these countries being in sub-Saharan Africa [7].

Operations (or operational) research (OR) is a discipline that uses advanced analytical methods to better understand complex systems and aid in decision-making [8, 9]. OR uses a wide range of problem-solving techniques and computational methods, including computer simulation, mathematical optimisation, statistics and decision analyses, to help improve the operations of organisations. With its orientation towards improving efficiency, cost-effectiveness and decision-making, OR is particularly useful for analysing complex global health issues – especially in settings where the burden of disease is high but health systems are weak and resources limited. Despite the growing use of OR in global health, it is unknown how much of an impact OR is having in this important area as publications rarely discuss whether their findings were implemented or were influential in policy- or decision-making [10, 11].

The objective of this scoping review is to examine the extent, range and nature of operations research activity in global health, specifically within healthcare settings, health services delivery, and population health in LMICs. Our goal is to highlight the breadth of healthcare applications of OR in global health, both geographically and across application areas, and – through select case studies – discuss the impact such studies can have on improving healthcare and healthcare equity for communities and populations globally. We aim to encourage OR researchers and global health practitioners alike to continue to apply OR in global health, particularly in areas where OR-based studies may currently be lacking, and to consider sharing the impact of OR work more broadly so that others can learn from challenges and successes.

It should be noted that, in the context of global health, the term ‘operations research’ is sometimes synonymous with implementation research [12] and is used broadly to encompass cross-sectional, case-control, retrospective or prospective cohort analyses [13–15], as well as qualitative research methods [12, 16], all of which are valuable in studying the effectiveness of health services and programs within the day-to-day operating environments of routine practice. In this review, however, we focus on studies where analytical methods or modelling are used to explore health research questions with an orientation towards decision-making or the consideration of ‘what-if’ scenarios – in other words, modelling studies that are prescriptive in their recommendations.

The modelling realm of OR is of particular interest because it can help address global health questions not easily answered with other methods. For example, OR is beneficial in situations where conducting a real-world study might be considered impossible, impractical, too costly or unethical, such as when choosing between implementing policy ‘A’ or policy ‘B’, when controlled trials to compare a wide variety of available options would be unreasonable, when the disease or illness of interest takes years or decades to progress and the process of evaluating long-term outcomes would be long and expensive, or when simulating virtual cohorts of patients allows researchers to explore questions without ethical consequences. OR is also useful for framing complex financial evaluations, for example, determining the most cost-effective intervention among many options, establishing the optimal way to allocate a limited budget across multiple competing needs, or deciding whether a new intervention (e.g. a vaccine) can be implemented sustainably with limited funding. In LMICs, such OR analyses, which help narrow down the number of possible options or help inform where to focus efforts for more targeted studies, are even more important due to limited resources.

While OR in healthcare in the developed world has been extensively studied in recent years [17–22], the latest review of OR in healthcare in developing countries was published in 1993 [10]. A few recent review papers and bibliographies have explored the use of OR in developing countries; however, these did not specifically focus on healthcare and included several other sectors such as agriculture, energy and transport [11, 23–25]. Others have reviewed the use of OR within a very narrow area of global health (e.g. infectious diseases, particularly HIV) [26–30]. Several survey papers and special issues of journals have recently focused on the use of OR to address global health or humanitarian issues, but these were not based on systematic reviews of the literature [16, 31–33]. Given that the existing literature on this topic is sporadic, not comprehensive in the search strategy, and lacks depth in the analysis of thematic areas, we have chosen a broad scoping review approach. With this approach, we aim to build upon previous work by providing a systematic and comprehensive landscape overview of the use of OR in global health with a more rigorous analytic framework than has been previously performed.

The results of this scoping review are presented in four main sections. First, we present a global overview of the literature, which includes the distribution of OR studies across countries of different income classifications, over time, and across different methodological approaches. Then, we explore the use of OR in four
global health application areas with concrete examples in each category. In this review, we consider the four main application areas of global health to be (1) health systems and operations, (2) clinical medicine, (3) public health, and (4) health innovations – from the local to global level. Next, health equity, which is integral to the concept of global health and transcends all four application areas, is explored as a separate overarching theme using a subset of included studies. Health equity is not only a topic of growing interest globally, but is compelling to explore through an OR lens. For example, when health equity is operationalised and quantified using meaningful and measurable criteria [2], OR methods can be used to analytically find solutions that improve or maximise equity. To our knowledge, the use of OR to analyse issues of health equity has not yet been explored through a systematic review. Finally, by way of selected cases, we present a discussion on implementation and impact, i.e. how OR has influenced real health policy change or aided in decision-making by stakeholders. We highlight common factors among these studies that likely helped contribute to their effective translation into policy or practice, and discuss barriers and challenges to bridging the gap between OR and health policy. We conclude the paper with a discussion of key insights and implications of this review.

Methods
We followed the scoping review framework set out by Arksey and O’Malley [34] and by others who have proposed refinements to this approach [35–37]. Specifically, we followed these five stages: (1) identifying the research question; (2) identifying relevant studies; (3) study selection; (4) charting the data; and (5) collating, summarising and reporting results.

Stage 1: Identifying the research question
This scoping review seeks to identify the extent, range and nature of OR in global health (i.e. geographical, over time, methodological and across application areas), with an in-depth exploration of literature addressing questions of health equity and literature having made a specific impact in decision-making or policy change.

Stage 2: Identifying relevant studies
The databases HealthStar (a subset of Ovid Medline focused on health systems research), Scopus, Web of Science, Inspec and Compendex were chosen to capture literature from multidisciplinary sources across health research and engineering. Individualised search strategies were designed for each database. We searched titles, abstracts and keywords for combinations of search terms in the following categories: OR modelling and methodologies; healthcare settings, health services delivery, and population health; LMICs and regions (e.g. sub-Saharan Africa, South East Asia, etc.), including specific country names in these income categories; and policy- and decision-making. The search strategy including all search terms for the Web of Science database is provided in Box 1 as an illustration, and all others are provided in Additional file 1: Tables S1 to S4. Only papers published in the year 2000 and later were included. This search strategy was refined and validated by ensuring the search captured a set of 15 ideal target papers [38–52] known to the authors. Librarians specialising in both engineering and health sciences literature were consulted when designing the search strategy. Search results were downloaded in August 2014. We also hand-searched 19 review papers and special issue articles [11, 13, 16, 17, 19, 23–33, 53–55] for additional references.

Box 1 Example search strategy for Web of Science database

| Database: Web of Science (WOS) |
| Strategy: Keyword search, “Topic search” (TS) was used, which searches all words in article titles, abstracts, author keywords, and “KeyWords Plus” fields. Sub-search categories: (a) model types, (b) geographic focus, (c) health, and (d) decision-/policymaking. Terms within categories were combined with “or”, and categories were combined with “and”. All LMIC names individually listed since country names are not controlled vocabulary in WOS. Results pre-2000 and unrelated WOS categories were excluded. |
| Sub-search categories: (a) Model types |
| TS=('operation*' research*) OR TS=(model* NEAR/5 (mathematical or queu* or inventory or scheduling or demand or forecast* or comput* or network or stochastic or decision* or delivery or simulation or optimisation or non-linear or nonlinear or linear or Markov or cost-effectiveness or agent-based)) OR TS=(optimisation$ NEAR/5 (mathematical or nonlinear or non-linear or linear or network or discrete or multicriteria or multi-criteria or stochastic or problem or minimisation or maximisation or location or allocation)) OR TS=(simulation NEAR/3 (comput* or discrete or agent-based or system$)) |
| AND |
| (b) Geographic focus |
| TS=('developing countr*' OR “low-income countr*' OR “middle-income countr*' OR “developing world” OR “developing nation” OR “low-resource setting” OR “resource-constrained setting” OR “resource-poor setting” OR “limited-resource setting” OR “resource-limited setting” OR “under-developed countr*' OR “least-developed countr*' OR “less-developed countr*' OR LMIC* OR Africa* OR Asia* NEAR/2 south) OR (Asia* NEAR/2 east) OR (Latin America* OR “central America*” OR “south America*” OR Caribbean OR “middle east”) OR (all low- and middle-income country names listed out) |
| AND |
| (c) Health |
| TS=(health* or medical or hospital or clinic* or treatment) OR AD=(health or hlth) |
| AND |
| (d) Decision-/policy-making |
| TS=(policy* or decision-making* or decision-support or decision-process or decision-aid* or implement* or impact) OR AD=(policy) |
Search results from each database were combined and duplicates were removed. An initial screen of the remaining 14,518 references eliminated studies that were clearly not relevant to this review. This initial screen was largely based on title and keywords; if additional information was required to judge relevance, the abstract was consulted. A large proportion of papers rejected at this stage fell into one of two categories, either (1) field studies and implementation research that did not have a modelling element, or (2) health-related modelling studies that were purely explanatory or descriptive in nature and did not have an orientation towards policy- or decision-making. There were 1408 abstracts remaining after this initial screening, including 31 articles from hand-searching review papers (Fig. 1).

Stage 3: Study selection
A second screen was conducted whereby a more rigorous set of inclusion criteria was applied to identify the final set of papers for the review. Two co-authors independently reviewed each abstract against the following four key inclusion criteria: (1) the study clearly used methodologies common to the field of OR; (2) the problem or research question was of an OR nature; (3) the study was related to a healthcare or public health issue; and (4) the geographic focus was on LMICs and/or regions (Box 2). For each main criterion, at least one of the sub-points had to be true in order for a paper to be included in the review. Papers for which both reviewers were in agreement were automatically included. Discrepancies were resolved through discussion (with a third reviewer if necessary), or by downloading and reading the full-text. Co-authors met periodically during this stage to discuss any uncertainties related to study selection and ensure consistency in applying the criteria. After applying the inclusion criteria, 1099 papers remained – these comprised the set of studies for our global overview.
Inclusion criteria for second screen of review process

1) An operations research (OR) technique is used
   — Simulation model (e.g. discrete event, agent-based, etc.)
   — Optimisation model (e.g. linear and non-linear programming, goal programming, location-allocation models)
   — Decision analysis, decision tree models
   — Stochastic, compartmental, state transition models (e.g. Markov)
   — General mathematical or probabilistic models of disease progression and/or transmission will be considered if Criteria 2 is met

and

2) An OR problem is explored:
   — Several competing interventions and/or policy options are modelled/simulated/compared to propose the best/optimal strategy (incl. comparing current status quo vs. a new option)
   — The cost-effectiveness of a treatment or intervention is explored through hypothetical cohorts of patients or through decision-analysis techniques to estimate costs per person
   — Outcomes are modelled for different treatment or therapy scenarios/options
   — Issues of logistics, supply chain, distribution, scheduling are explored; including studies that highlight operational inefficiencies or poor performance
   — ‘What if’ scenarios are tested, e.g. what if anti-retroviral therapy coverage was increased?

and

3) The OR problem has a healthcare delivery or public health focus
   — Health services delivery (hospital/clinical services, primary care, or treatment or diagnostic options, health technology management or integration, etc.)
   — Public or population health (vaccination policy, mass screening for health conditions, transmission prevention and/or reduction, etc.)

and

4) The study focuses on a low- or middle-income setting
   — Country-focused: a look-up table was provided to co-authors to determine whether a country was low income, lower-middle income, or upper-middle income
   — Regional: Africa, sub-Saharan Africa, South East Asia, Latin America, South America, etc.

Stage 4: Charting the data

‘Charting’ is “a technique for synthesising and interpreting qualitative data by sifting, charting and sorting material according to key issues and themes” [34]. For each of the studies included, the following items of information were charted by one co-author and cross-checked by another: (1) country or region of focus; (2) income classification of that country; — low income, lower-middle income, or upper-middle income; (3) OR methodology or type of OR model developed/used for the analysis; (4) health issue studied (HIV/AIDS, malaria, childhood pneumonia, etc.); (5) application area of global health – Health Systems and Operations, Clinical Medicine, Public Health, or Health Innovation; and (6) level at which the study was targeted – local, national, regional, global or general. These characteristics were gathered from the abstract, but in cases where this information was not clearly stated, the full text was consulted.

The Health Systems and Operations category refers to studies that looked at the logistics related to the provision of services, the allocation of resources or the operations of health facilities. Clinical Medicine was distinguished from public health in that these studies focused primarily on disease diagnosis, treatment or care for the individual patient (e.g. treatment regimens, case management, etc.), whereas Public Health studies emphasised disease prevention and health promotion at the community or population level (e.g. vaccination policy, mass screening, etc.). The Health Innovation category was reserved for studies that explored healthcare innovations or technologies in the pre-implementation stages of development (e.g. vaccines still in early clinical trials and not yet accepted for widespread use, hypothetical future discoveries – in diagnostic, treatment or vaccine technologies). The study’s target level refers to the level at which the model recommendations would be or were intended to be implemented. ‘Regional’ refers to

To identify papers among the 1099 studies in the global overview that explore the specific theme of health equity, we searched for the following keywords within titles, abstracts and author addresses: (in)equity*, (in)equalit*, pro-poor, poorest, socio-economic, marginalized, stigm*, quintile*, disparit* and gender. Two co-authors assessed each abstract and collaboratively decided if they addressed an issue aligned with the definition of health equity as described by Braveman and Gruskin [2]. Full-texts for health equity-themed papers were downloaded and read.

Identifying studies for the impact theme was less straightforward. As noted by others who have reviewed OR in global health or LMICs [10, 11, 23, 24], many OR studies are published before any evidence of having influenced policy- or decision-making has been demonstrated. Thus, it would be misleading to assess the impact of OR studies based solely on a review of published literature. We therefore took the approach of providing select case studies of studies where impact was described in the publication in order to gain insight from their experiences, with the caveat that additional OR studies have likely had an impact on improving global health. For our purposes, ‘impact’ implies that study results meaningfully informed a policy decision, or that model recommendations were implemented in a real-world situation. Full-texts for impact-themed papers were downloaded and read.
global regions (e.g. sub-Saharan Africa, South-East Asia) and not sub-national regions. The ‘general’ category was reserved for those studies that considered ‘low-resource settings’ as the target in a very general sense or where the level of intended implementation was not clear.

For the most part, studies were easily categorised; however, a small fraction fell into grey areas. Where there was overlap, a determination was made based on what was deemed to be the dominant category. For example, studies that were based on a local setting but were intended to inform national policy- or decision-making were counted towards the national category because proposed changes would be made at the national level. Similarly, some studies bridged clinical and public health (e.g. screen and treat programs). We considered any study with broad public health goals, regardless of whether treatment was included, as public health.

Stage 5: Collating, summarising and reporting results
Based on Arksey and O’Malley [34], we present our findings in two ways. First, through basic numerical analysis of the extent, nature and distribution of studies across various dimensions (i.e. global overview, application areas), and second by organising a subset of the literature thematically (i.e. for the themes of health equity and impact).

Results
Global overview
In this section, we present a global overview of the 1099 studies that met the inclusion criteria, including a breakdown of OR studies according to country income classifications, geographic regions, year of publication and methodology.

Figure 2 shows the breakdown of OR studies by country income level. The majority of studies (74%) were focused on a specific low, lower-middle, or upper-middle income country; however, several studies (20%) were targeted towards LMICs broadly, and a small proportion (6%) looked specifically at a grouping of countries or regions that spanned several income categories (Fig. 2a). Among the 817 studies that had a single-country focus (Fig. 2b), low-income countries made up 17% whereas middle-income countries (lower-middle and upper-middle) made up 83%, with the majority being in the upper-middle income category. Using number of countries and population as benchmarks, our findings suggest that lower-middle-income countries are under-represented in the literature, upper-middle-income countries are over-represented, and the representation of low-income countries is roughly proportional to these benchmarks. Lower-middle-income countries make up about 34% of all LMICs and 44% of the LMIC population but only 18% of the literature, while upper-middle-income countries make up 40% of all LMICs and 41% of the LMIC population but 65% of the literature. For comparison, low-income countries, which make up 17% of the literature, represent approximately 26% of all LMICs globally and 15% of the LMIC population.

Figure 3 provides a more detailed geographical view of the distribution of OR studies across the developing world. Almost 40% of the literature reviewed was focused on just six LMICs. China, Brazil and South Africa were the most frequently studied, and collectively accounted for 25.4% of the studies reviewed. India, Mexico and Thailand accounted for 14.5%; all were classified as upper-middle-income countries, except India, which was a lower-middle-income country. These countries represent just 4.4% of all LMICs, but account for about 52% of the total LMIC population. The low-income country most studied in the OR literature was

！Fig. 2 Breakdown of operations research studies according to World Bank income classification of the country of focus – low-income (L), lower-middle-income (LM) or upper-middle-income (UM) – for (a) all studies (n=1099) including studies about low- and middle-income countries in general or some combination of regions and/or L-, LM- and UM-income countries; and (b) studies focused on a single country only (n=817)
Uganda, with 26 studies. More papers were focused on Asia and South America than sub-Saharan Africa (excluding South Africa). Approximately 50 LMICs were not studied in any of the global health OR publications identified; these countries account for approximately 5% of the total LMIC population, or approximately 303 million people.

As Fig. 4 suggests, low- and lower-middle income countries have historically been less frequent targets for global health-related OR compared to upper-middle-income countries. Despite a steady increase in the absolute number of studies focused on low-income countries since 2000, the proportion of such studies relative to all global health-related OR has plateaued at approximately
14% since the year 2006. This figure also suggests a trend towards more country-specific analyses rather than studies that consider LMICs in general or groupings of countries (see Other category in Fig. 4). A possible explanation for the drop in number of papers for 2013 is the lag between when a paper is published versus when it has been indexed in databases. The year 2014 was not included in Fig. 4 since our review does not encompass the entire year.

A breakdown of OR studies according to methodology is shown in Fig. 5. A wide range of OR methods have been used to study global health issues, and no single method appears to be dominant. In the section that follows, examples of different methods are provided within the context of four application areas of global health.

Global health application areas

In this section, we explore the volume and breadth of OR literature found across two dimensions of global health: the global health application area and the level at which the analysis was targeted (Fig. 6). These application areas were chosen because we felt they were broad enough to cover the full gamut of global health challenges. At the same time, studies within categories would carry a similar flavour in the types of problems studied. Other categorisations could also have been appropriate [10, 16]. Similarly, we felt it important to distinguish between different levels of focus as the types of problems, analytical approaches, and scale of implementation would be different across these levels. Detailed examples of OR studies in the four areas of global health are described in more detail in the subsections that follow.

The majority (58.3%) of OR literature explores clinical medicine and public health issues at a national level, with locally-focused health systems and operations studies being the next most frequently studied area (11.0%). Since policies affecting clinical medicine and public health are typically mandated by national ministries of health or implemented by national public health programs, it makes sense that the OR studies in these areas have been targeted at the national level. Although very helpful for exploring the impact of interventions on a macro scale or adding to discussions on global priority setting, fewer studies were targeted at the regional or global level (12.2%) or towards LMICs in general (6.8%).

Health systems and operations

About 20% of the literature was related to health systems and operations, and most of these studies were focused on the local or national level. At a local level, common analyses included improving the day-to-day operations of health facilities (e.g. patient flow and wait times in health facilities [49, 56–60] and emergency departments [61–64], facilities layout planning [65, 66], inventory planning [67, 68], nurse rostering [69–75], and surgical scheduling [76–79]) and health services planning (e.g. location-allocation of emergency medical services [80–82] or new health facilities [83–86]). The majority of these types of problems were analysed using simulation (25.0%) or optimisation (35.0%), or a combination of both methods (3.3%). For example, discrete-event simulation (DES) was used to analyse patient wait times in health clinics in Zambia [49] and Colombia [59], and a combination DES-optimisation model was used to study ambulance positioning and response time for an urban city in Brazil [81].

At the national level, questions related to supply chains and logistics were often explored using methods such as agent-based simulation, DES and other types of microsimulation. For example, a series of recent studies used the HERMES (Highly Extensible Resource for Modeling Event-Driven Supply Chains) software to develop DES models of the vaccine supply chain in Niger and Thailand; researchers explored the impact on vaccine availability of introducing new vaccines into the supply chain [87, 88], changing vaccine vial size or replacing multi-dose vials with single-dose vials [46, 89], removing the regional level of distribution [90], and trade-offs between augmenting transport versus increasing cold storage capacity [47, 91].

The lack of adequate resources represents a major constraint for health systems in LMICs, thus the
efficiency with which available resources are being used was another common theme. A small subset of OR literature (2%) used data envelopment analysis at both a local and national level to analyse the efficiency of health facilities and systems in many low-resource settings. ‘Technical efficiency’ is typically defined as a ratio between a weighted sum of outputs (e.g. number immunisations provided, number of antenatal visits, etc.) and a weighted sum of inputs (e.g. human and financial resources, supplies, beds, etc.); a less than ideal efficiency, as indicated by an ‘envelope’, indicates that a health facility can potentially expand their outputs without changing the quantity of inputs used [92]. Data envelopment analysis studies have been set in India [93–95], Kenya [96, 97], Sierra Leone [98], Angola [92] and Zambia [99], and helped identify inefficiencies in health services delivery, as well as opportunities to better use existing resources. Other studies exploring efficient resource allocation included a simulation model used to provide insight into better resource utilisation (e.g. personnel and physical resources) in an emergency department in Malaysia [100], and an optimisation model used to explore the optimal allocation of resources in a region in Tanzania given different health objectives (e.g. minimise number of deaths, minimise disease incidence, minimise loss of quality of life, etc.) [101].

One area of health systems and operations that was not often studied using OR was medical equipment and health technology management. In addition to two previously mentioned studies about increasing vaccine cold storage equipment [47, 91], we identified just nine OR studies related to medical equipment. Some examples include a cost-utility analysis of introducing PET scanning technology for lung cancer diagnosis in Iran [102]; a queuing model developed to improve response and turn-around time of equipment repair work orders in a clinical engineering department in Cuba [104]; and models to help inform general medical equipment purchasing [105] and replacement schedules [106] in LMICs.

Clinical medicine
Most clinical medicine studies were focused at the national level. Common themes were assessing the cost-effectiveness of adopting new treatment or diagnostic strategies, comparing outcomes or cost-effectiveness of competing treatment options, and estimating the benefits of scaling-up treatment access.

Almost 45% (168) of studies in this category were related to HIV/AIDS, malaria or tuberculosis (TB). For example, STDSIM [107] – a microsimulation decision-support model – has been used in several studies to analyse the impact of expanding anti-retroviral (ARV) access [108, 109] as well as treating other curable sexually transmitted infections in order to prevent HIV infection [110–112]. Shillcutt et al. [113] used a decision-tree model to evaluate the relative cost-effectiveness of presumptive treatment, field standard microscopy, or rapid diagnostic tests for malaria diagnosis in different sub-Saharan African settings. A combination decision analysis and Markov model was used by Mandalakas et al. [114] to compare the cost-effectiveness of different TB prevention strategies using WHO-recommended isoniazid preventive therapy for children in close contact with infectious TB cases.

Stochastic models, such as Markov models, were common methods for clinical studies, representing almost 26% of the studies in this category. Such models are useful for simulating cohorts of patients with a specific illness as they transition from one disease state to another.
throughout the course of an illness or even their lifetime. For example, the cost-effectiveness of different treatment options for patients with chronic hepatitis B was studied using Markov disease models in China [115, 116], Brazil [117, 118], Turkey [119] and India [120], over time horizons ranging from 20 to 40 years.

Interestingly, 53 of the 70 studies related to the diagnosis or treatment of cancer, cardiovascular disease or diabetes were published in the past 5 years (between 2009 and 2014), consistent with increased global attention on such non-communicable diseases in LMICs [121, 122]. For example, a Markov model was developed to compare the cost-utility, in terms of quality-adjusted life years, of four different treatment options for lung cancer in Thailand [123]. DES models were used to analyse the cost-effectiveness of saxagliptin as a treatment for type II diabetes in both Argentina [124] and Brazil [125]. The treatment of mental health issues is one area that has not been studied extensively with OR – we found only 13 studies in the clinical medicine category that focused on mental illnesses in LMICs such as depression and schizophrenia.

Public health
Public health, specifically at the national level, was the most common global health area explored using OR. Vaccination policies, particularly the introduction of vaccines into routine child immunisation programmes, and other disease prevention strategies such as screening programs (e.g. for cervical cancer), were among the most common types of problems explored.

An example vaccination model is the TRIVAC decision-analysis model from the Pan American Health Organization ProVac initiative, which was used to assess the cost-effectiveness of adding vaccines (e.g. pneumococcal conjugate vaccine, Hib and rotavirus) to the routine child immunisation schedule in LMICs, particularly in Latin America [126, 127]. Among preventative public health measures, studies exploring screening and/or vaccination combinations were common. For example, Demarteau et al. explored efficient combinations of cervical cancer prevention strategies (e.g. screening and/or vaccination against human papillomavirus) using a combination Markov and optimisation model, in both Brazil [128] and Nigeria [129]. The Markov model estimated the costs and outcomes of different strategies, which was used as input to an optimisation model that determined the combination of prevention strategies that minimised cervical cancer cases for a fixed budget.

Similar to the clinical medicine category, HIV/AIDS, malaria and TB were a common focus for public health studies, with approximately 30% of all studies in this category dedicated to these illnesses. Simulation platforms, such as OpenMalaria [130] and STDSIM [107], have provided the modelling foundation for several public health-oriented OR studies related to such illnesses, at both a national and regional level. STDSIM was used to analyse focused public health interventions for high risk groups such as commercial sex workers [131, 132]. The OpenMalaria model was used to simulate the impact of interventions such as indoor residual spraying in the highlands of western Kenya [133].

Global-level studies represented only 2% of studies, and most of these (52%) were in the public health category. Examples of such studies include a model to recommend the required size and resulting cost of an international stockpile of cholera vaccine to enhance efforts to mitigate cholera outbreaks in the wake of natural disasters [134], and a comparison of the potential impact of rotavirus versus human papillomavirus vaccination across 72 countries eligible for support from the Global Alliance for Vaccines and Immunization (GAVI), taking into account affordability, cost-effectiveness and distributional equity [135].

One area of disease prevention that lay at the intersection of clinical medicine and public health is the prevention of mother-to-child transmission of HIV. Although some prevention strategies are of a clinical nature (e.g. administering ARVs or nevirapine), we considered this a public health issue as there are other behavioural considerations as well (e.g. recommendations for early weaning or avoidance of breast-feeding). Examples of such studies include a DES model used to evaluate relative benefits of ARVs at childbirth and/or bottle-feeding in Tanzania [45], a mathematical model comparing different feeding recommendations (i.e. exclusive replacement-feeding versus exclusive breast-feeding for durations of 4 or 6 months) at different compliance levels in Uganda and Kenya [136], and simulation studies exploring the cost-effectiveness of implementing the WHO’s 2010 guidelines for the elimination of mother-to-child transmission in Zimbabwe [137, 138].

Health innovation
Innovation was the least studied category of global health-related OR, with only 47 papers. The majority of these studies (89%) were related to vaccines, either in the early phases of clinical trials or yet to be developed, and were predominantly focused on HIV and malaria. Common themes were modelling the potential impact of imperfect or partially effective vaccines [139–143] or vaccines with rapidly waning protection [144, 145], modelling changes in behaviour (i.e. adopting riskier or relaxed behaviour) with the introduction of a newly developed vaccine [146–149], modelling the cost-effectiveness or willingness-to-pay thresholds of a new
vaccine [150–157], forecasting demand for a new vaccine [158], or combinations of these issues [159–165].

Some studies explored the best ways to implement or roll-out a new vaccine should it become available (e.g. through the Expanded Programme on Immunization (EPI), school-based programmes, mass vaccination campaigns, targeted high risk groups, planning for follow-up boosters, etc.) particularly in cases where initial supplies are expected to be limited [166–171], as well as how a partially effective vaccine would measure up against existing prevention strategies [172] (e.g. male circumcision in the case of HIV [173] or insecticide-treated nets in the case of malaria [174]). Lee et al. [175] used a DES model of næril’s vaccine supply chain to analyse the impact of developing thermostable versions of six currently available EPI vaccines, an innovation that could relieve bottlenecks in the cold chain. They found that thermostable versions of any of the EPI vaccines, either individually or in combination with other vaccines, would decrease cold storage and transport utilisation and increase the availability of all vaccines, even non-thermostable ones. Levin et al. [176] also explored thermostable vaccine introduction in Cambodia, Ghana and Bangladesh – their model was a spreadsheet-based decision tree and costing analysis.

Other studies examined innovations in drugs and new diagnostic technologies [177–179]. For example, Dowdy et al. [178] used a decision analysis model to estimate the cost-effectiveness of a novel point-of-care TB diagnostic tool in comparison to existing methods in South Africa, Brazil and Kenya. Cost-effectiveness was sensitive to the specificity and cost of the new test, but its introduction was estimated to avert almost 50% more disability-adjusted life years per 1000 TB suspects [178].

The examples provided in this section highlight how OR can be a useful tool for informing health policies and decision-making in low-resource settings – from studies with local health facility-level implications to analyses that are global in scope, exploring issues that span all application areas of global health. We have highlighted areas where there has been a strong OR focus; for example, national-level studies focused on clinical and public health and studies about infectious diseases such as HIV/AIDS, malaria and TB. Areas where OR analyses have been lacking include health technologies and non-vaccine-related innovation, and non-communicable diseases such as cancer, diabetes and mental health.

Health equity theme
This section focuses on an important goal of global health – achieving equity in health for all people worldwide. The challenge in studying health equity is that there is no single way to identify or measure it within a community or population. We felt it would be compelling to discuss how issues of health equity have been analysed using an OR approach, especially given this challenge.

Out of the 1099 papers included in this review, we identified 44 studies that considered health equity as an important part of the research question being explored. Due to our review’s focus on healthcare provision and public health, rather than wider social determinants of health, the studies in this section are primarily focused on healthcare equity, specifically as it relates to socially disadvantaged groups. These studies spanned all four application areas of global health (health systems and operations (n = 16), clinical medicine (n = 4), public health (n = 22) and innovation (n = 2)) and all target levels (local (n = 6), national (n = 29), regional (n = 3), global (n = 4) and general (n = 2)). Geographically, studies were predominantly focused on South Africa (n = 10), China (n = 5) and India (n = 4); all other locations had just one or two studies.

Studies differed in how they operationalised (i.e. defined the measurement of) healthcare equity. Some studies defined inequity as a quantifiable disparity in a specific health indicator across different social groups (e.g. mortality risk across wealth quintiles [180], malaria incidence in children and pregnant women vs. adults [181]) and estimated how this indicator might change with a more equity-centred approach to an intervention. Other studies parameterised equity as a model variable that ranged between two extremes – from least to most equitable (e.g. percent coverage of an intervention [182, 183], measures of spatial accessibility [184] or a modified Gini coefficient [185]) – allowing researchers to explore the circumstances under which this parameter was less than ideal or even how to maximise it. Some applied a single ethical principle when operationalising equity (e.g. Wilson et al. [183] took an egalitarian approach), whereas others explored their research question through multiple ethical lenses [185, 186].

We also looked at the distribution of healthcare equity studies across groups with different levels of underlying social advantage/disadvantage, including wealth, geographic location, sex or other social status (Fig. 7).

Accessibility of healthcare, for both the financially and geographically disadvantaged, was a common theme among equity-related papers. The impact of health insurance and/or universal coverage [185, 187–189], user fees [190] and subsidies [191] on equitable healthcare accessibility and affordability was one of the most prominent themes. For example, Waters et al. [185] used a statistical probit model to analyse the potential impact of a health insurance program and various insurance eligibility standards on both overall access to healthcare, as well as equitable access to healthcare across all
economic quintiles in Ecuador. Economic status was also considered by Pagel et al. [192], who explored how different community-based strategies to prevent postpartum haemorrhage affected women of different economic quintiles in Malawi, and Carrera et al. [193], who showed that an equity-focused approach to child health that prioritises the poorest and most marginalised populations could lead to higher decreases in child mortality while being more cost-effective than traditional approaches.

Geographic accessibility and distribution of health services, and the identification of geographic disparities in health, were explored by a number of resource location-allocation studies [183, 184, 186, 194–196]. For instance, Moore and Stamm [184] built a location optimisation model for cholera treatment facilities in Haiti, using the Enhanced Two-Step Floating Catchment Area method. They present their model with five unique objective functions, including one that minimises inequitable access, in order to explore the trade-offs between adequate, equitable and efficient coverage of treatment centres. Similarly, a resource allocation model of a Zambian health service delivery program parameterised equity in the objective of their optimisation model for decision-making based on resource efficiency and equity across varying geographic locations [186]. In India, a location-allocation model was used to propose new health facility locations for improved geographic access to healthcare [194].

Health equity issues related to sex [146, 197–204], high-risk groups (e.g. commercial sex workers) [205–207] or marginalised groups (e.g. people living with HIV) [182, 208–212] were commonly associated with health issues such as HIV and cardiovascular diseases. For instance, upon recognising that women often lack the power to negotiate safe sex in developing countries and can be exposed to HIV against their will, studies have analysed the effects of post-circumcision changes in male condom use [198, 200] and women-initiated vaginal microbicides [199] on gender health equity in Southern Africa. The issue of high HIV burden among sex workers was analysed using a deterministic model that compared the impact of several interventions, including equitable access to ARVs and community empowerment programs that educate female sex workers about preventive measures against HIV [207]. Two studies applied an equity lens to mathematical optimisation problems exploring optimal HIV treatment strategies in South Africa [182, 183]. Wilson et al. [183] formulated an ‘equity objective function’ to propose ARV allocation strategies that would ensure each individual infected with HIV has an equal chance of receiving ARVs. Cleary et al. [182] parameterised the concept of health equity as the percent coverage of treatment in HIV/AIDS patients. By placing different constraints on this parameter in the model, they were able to highlight the trade-off between maximising equity versus maximising health outcomes, where the ‘opportunity cost’ is QALY’s forgone in the former scenario, and higher proportions of unmet need in the latter [182].

These examples highlight the utility of OR for informing equitable health policy decision-making in low-resource settings. Equity is not a concept easily measured, nor will it be possible to achieve consensus on how it should be measured. A major contribution of OR is that it allows for equity to be quantified in different ways, often within the same modelling framework, such that trade-offs and consequences can be explored more systematically, opening up important discussions about how best to reduce systematic disparities in health for all people worldwide.

Impact theme
In this section, we highlight seven OR studies in which the authors described how their work was implemented or was influential to specific health policy changes or decisions. This compilation is not an exhaustive list;
however, studies describing implementation or impact represent a very small fraction of all papers in this review (we estimate less than 10% based on our review of abstracts). In the sub-section that follows, we explore several features of these studies that may have helped contribute to the effective translation of model recommendations into policy or practice, and discuss barriers and challenges to bridging the gap between operations research and health policy.

**Case examples of OR impact**

The first four studies are examples of impact at the national or global level. Dowdy et al. [213] used a decision tree model to estimate the cost-effectiveness of serological testing for active TB in India. Serological tests are widely used in India and other developing countries because they are fast, simple and readily available; however, no international guidelines recommend their use over other diagnostic tests such as sputum smear microscopy. The study found that serology tests can result in more secondary infections and false-positive diagnoses, and cost more per-patient, compared to sputum smear microscopy. Their findings, which were presented to a WHO Expert Group on TB in 2010, were influential to the WHO’s subsequent policy statement recommending against the use of commercial serological testing for active TB [213].

Hutton et al. [38] developed a combination decision tree and Markov model of hepatitis B infection and progression, which compared options for hepatitis B screening, vaccination and treatment in the United States and China. In China, they found that providing catch-up vaccination for children under 19 would improve health outcomes as well as save healthcare costs in the long run due to the number of infections averted. Their modelling work in 2008 was influential in China’s decision to expand free catch-up vaccination to all children under 15 in April 2009 [38].

In the wake of a global debate to shift the significant resources being used for polio eradication towards effective control [214], a systems dynamics disease outbreak model for polio developed by Thompson and Tebbens [215, 216] demonstrated that shifting to a control strategy would not only be more costly in the long run, but would lead to more cumulative cases as populations become more susceptible to new outbreaks [215]. After the results of their model were presented to global stakeholders at a WHO-convened consultation in 2007, experts were convinced that efforts towards completing eradication must continue; for example, the director of the global polio-eradication initiative at the WHO in Geneva commented that Thompson’s work put “a nail in the coffin for the idea that there is a cheap and painless way out”, and a representative from the global immunisation program at the United States Centers for Disease Control and Prevention commented that this analysis showed there is no viable control option and that we need to intensify eradication efforts [217]. As eradication efforts continue today, there is hope that complete eradication can be achieved in 2016; in 2015, there were fewer cases in fewer countries than ever before, and in January 2016, India marked its fifth year without a case of polio [218].

A DES model was developed by Langley et al. [39] to evaluate the impact of automated nucleic amplification test (aNAAT), a new TB diagnostic test, compared to existing techniques in Tanzania. The model recommended several combinations of TB diagnostic options incorporating aNAAT testing that were cost-effective in both urban and rural settings. At the time of publication, policymakers in Tanzania were considering specific sites for a trial of the new aNAAT technology, and results from the DES model were going to be used to inform the implementation plan for the trial [39].

The following three studies are examples of implementation on a more local level. Cruz et al. [104] developed a queuing simulation model to help enhance medical equipment repair service quality for the clinical engineering department of a 600-bed hospital in Cuba. Simulation results showed that service quality enhancements (i.e. reduced work order backlogs and service times) could be achieved without hiring new personnel. Clinical engineering management implemented two proposed strategies and major service improvements were observed over a 2-year period, as predicted by the model [104]. Perez et al. [59] used a combination DES-optimisation model to reduce wait times in the admissions centre of a health centre in Colombia with relatively low additional cost. The solutions proposed by the model were subsequently implemented, and although not explicitly measured, experts in the admissions centre noticed relevant improvements in wait times [59]. Finally, Friedrich et al. [72] developed a decision support system (DSS) using linear programming to upgrade the nurse scheduling process at a hospital in South Africa in order to improve the quality of healthcare and nursing services. The model’s objective was to minimise nurse dissatisfaction by better taking into account nurse preferences. Although the system had not been fully implemented at the time of publication, feedback provided through user validation was positive and enthusiastic. Staff managers reported that, in just a few seconds, the system performs the same time consuming computations they carry out manually each month, with improved nurse utilisation and reduced overtime [72].
Factors contributing to success in ‘bridging the gap’ between OR and impact

Based on these cases, three key drivers for bridging the gap between OR and impact have emerged, namely (1) engagement of local or expert stakeholders in model design and validation, particularly those in policy- or decision-making roles; (2) use of contextually representative data; and (3) a concentrated effort on communication of research findings. All selected cases demonstrated all three of these key drivers even if not explicitly cited in the discussion that follows.

(1) Local or expert stakeholders involved in OR model design and validation Active participation of local stakeholders has been suggested by others as a key to strengthening health research and policy linkages [219, 220] and the examples provided in this section are evidence of this in the field of OR. Such collaborations are important for several reasons. First, the engagement of stakeholders facilitates the identification of relevant and appropriate global health research questions. Thompson and Tebbens advise that “modelers need to focus on working effectively with the people who need and can use the results” [215]. Langley et al. [39], who underwent a comprehensive review of the questions that policymakers need to address when assessing different TB diagnostic strategies, are a great example of this. Situating their work within this ‘Impact Assessment Framework’ [221] not only helped identify the questions that their model should answer, but also informed the appropriate choice of modelling methodology to achieve their goals. Identifying relevant research questions is perhaps more easily accomplished for OR studies based on local settings. For example, Friedrich et al. [72] conducted a root cause analysis of challenges faced at the hospital they wanted to help, and developed their decision-support solution in response to several identified problems around nurse scheduling. Cruz et al. [104] and Perez et al. [59] also worked with local collaborators to identify and model relevant problems for the health facilities they worked with.

Second, it is critical to involve local or expert collaborators in the model conception and design because they are intimately knowledgeable about the context, and can help ensure that the model and analysis accurately describes the health issue and addresses the policy questions or decisions they face. This type of collaboration was demonstrated by Hutton et al. [38], who formed a multi-disciplinary team, including the director of Stanford’s Asian Liver Centre, for their research on hepatitis B in China. They also used an iterative approach to model development, beginning with a very simple representation of patient health states, with details added incrementally based on suggestions from experts until they were satisfied that their model appropriately represented the policy problem [38]. Friedrich et al. [72] also underwent an iterative design process, whereby their nurse scheduling DSS model was tested with users and continuously improved throughout development. Langley et al. [39] worked with experts from Tanzania and Malawi to ensure the input parameters and control logic for their DES model were valid.

Third, engaging local stakeholders throughout the development process can also facilitate trust-building and implicitly lead to capacity building, helping to address the lack of technical ability to interpret findings common in LMICs [219] and empower the policymakers to take ownership of the process. For example, as a result of the work by Langley et al. [39], policy advisors in Tanzania have requested the ability to be able to use the simulation model themselves to evaluate alternative diagnostic strategies in the future. A pilot study is underway to demonstrate whether the model is sufficiently user friendly for this type of use [39]. In the case of Friedrich et al. [72], the users were pleased that their input was used so extensively in the development of key features of the nurse scheduling DSS, including the interface design and the data validation function that prevents them from entering invalid data; users even requested further training in using the DSS [72].

If collaboration between local policymakers, researchers and implementers is important for impact, then the lack thereof can be a major barrier to impact. Yet, much of the OR literature reviewed did not have a collaborator or partner in the context where their model was intended to serve. Although some studies did express a desire to use their models and results as a basis for further research in partnership with healthcare organisations, in general, few of the studies in this review mentioned showing (or even the intention of showing) their model or results to relevant stakeholders.

(2) Use of contextually representative data In addition to having relevant stakeholders involved in the model conception and design, contextually representative data is also likely an important factor in generating OR analyses that have impact or are implementable. The featured case studies are examples of the use of appropriate data. The studies by both Thompson and Tebbens [216] and Dowdy et al. [213] were focused on India, and to the extent possible, were populated with input data relevant to the Indian context, from state-level statistics on population, polio incidence, etc. [216] to costing data obtained from local labs [213]. These nationally-focused studies were compelling enough to capture the attention of global stakeholders, such as the WHO, leading to broader global implications. Hutton et al. [38] conducted a comprehensive review of over 250 published papers to
populate the data for their model on hepatitis B in China. Input data for the TB diagnostics model in Tanzania came from a range of sources, including the National TB and Leprosy Programme, diagnostic centre laboratory records, and local managers [39].

For locally-focused studies, especially when local collaborators are involved in the research exercise, it is often possible to prospectively collect the data required for modelling. For example, Cruz et al. [104] used data collected in the hospital’s electronic technology management system over a 3-year period for both the development of their equipment service simulation model and for the validation of their model recommendations post managerial improvements. For the study to reduce wait times at a health centre in Colombia, the time between patient arrivals and service time in the admissions centre were collected for a short period of time in order to build the simulation model. The model was further validated using admissions data provided by health centre managers [59].

For many of the other studies in this review, assumptions and assumptions were required to estimate certain model parameters. Often researchers had to resort to the use of unrepresentative data, for example data from neighbouring regions or developed countries. These data assumptions and compromises, which are often unavoidable, should be taken into consideration when applying model results and recommendations to a given context.

Availability of reliable data is one of the challenges that sets low-income countries apart from middle-income countries with regards to modelling [32]. In this review, the studies in some middle-income countries (e.g. China [38] and Brazil [43]) were able to make use of centralised hospitalisation information systems and national household surveys, enhancing the validity and robustness of their models and analyses. In fact, access to data may be a reason for location selection on the part of researchers, possibly explaining our finding that low-income countries are less often targets for OR. For example, one study stated “India was selected for this simulation because it is one of the largest developing countries and sufficient data on breast cancer epidemiology to construct a reliable and valid model were available” [222].

(3) Emphasis on communication of research findings

Publication is important, but not sufficient, for the effective communication of research findings, whether from OR or other types of analyses. Communication in various forms beyond the journal publication was an important part of the case studies that influenced change. Perhaps the best example of this was Thompson and Tebben’s work on polio eradication [215], which they had the opportunity to present at a WHO stakeholder meeting in early 2007. For their presentation, they did not focus on explaining the model, equations, and diagrams in detail, but communicated the key insights in the simplest way possible [215]. For the study on TB serology testing, two of the authors were affiliated with the Stop TB Partnership’s New Diagnostics Working Group and had the opportunity to present their study findings to a WHO expert panel on TB serological testing, an audience that would be receptive to their work [213]. One study was actually translated into another language [38], and for another [72], user validation interviews were conducted in the local language in order to get the most accurate feedback possible from users.

Many of the OR models had user-friendly interfaces or used visual simulation environments as a means of communicating their model applications and results in a more personalised or accessible fashion. For example, Hutton et al. [38] specifically used Microsoft Excel because their intent was to develop a model that could easily be shared with policymakers. They “incorporated sufficient detail to capture important characteristics of hepatitis B disease progression and treatment so that the model would be believable to a clinical audience” [38] but tried to keep it simple enough so that those who lack modelling expertise could easily understand it. Langley et al. [39] also stressed the importance of a visual representation of the modelled processes in order to improve engagement and assist in the validation of their model with experts in Tanzania; the simulation software they chose afforded this possibility. The output of the nurse scheduling DSS model was formatted similarly to the hospital’s previous manual scheduling process so that unit managers would more easily adopt and transition to the new system [72].

Overall, the continued expansion of research reach and influence requires sustained efforts to communicate findings through different channels, with engaged outreach to, and personal connections with, policymakers and public health officials.

Discussion

“Scoping studies aim to map the literature on a particular topic or research area and provide an opportunity to identify key concepts; gaps in the research; and types and sources of evidence to inform practice, policy-making, and research” [35]. The goal of this scoping review was to provide a broad overview of the use of OR in global health, with several concrete examples showing the breadth and depth of how this field of research is being applied to important global health challenges worldwide. We also explored the theme of health equity, demonstrating the unique opportunities the field of OR can contribute to this increasingly important area of global
health. Cases where OR has had an impact on policy- or decision-making were also highlighted, with examples ranging from the implementation of local-level changes related to the day-to-day operations of health facilities, to decisions about national vaccination policies, to influencing international WHO policies and global perceptions about disease eradication. These cases serve as excellent examples of the importance of collaboration, data and communication for affecting change at the local and global level.

Limitations and challenges of the review
We faced some challenges and limitations when conducting this review. Given the broad interpretations of what constitutes OR, a lack of consistent terminology for OR, and the variety of journals where OR literature in healthcare tends to be published, our search terms were broad in reach and scope, with the consequence that a large amount of literature was captured that was not relevant. Additionally, the geographic search tailored to LMICs was not straightforward; country names are not always considered controlled vocabulary, so every individual country name had to be included as keywords.

We also had to be pragmatic at the outset about the coverage of the review. We chose to focus on papers published in the year 2000 and later. As such, there is some overlap with the hand-searched literature [11, 16, 17, 23, 24, 26–28, 32], but not with the review of OR in global health by Datta [10], which at the time of our review was over 20 years old. To fill this gap would have been an onerous task. Due to rapid advancements in computing technology, it could be argued that OR models developed before 2000 are out-dated, as are any global health data used to populate them. Further, we also had to be selective when setting the inclusion criteria for the types of ‘OR’ and ‘health’ studies explored given these terms have such broad definitions. We restricted OR studies to those where modelling or analytical methods were used with an orientation towards decision-making. Our health focus was largely on healthcare provision and public health, and did not include the wider social determinants of health; this focus was inherently reflected in the subset of studies explored for the health equity-theme as well. As it was, due to the volume of literature included, we could not summarise or cite all of the studies found; however, we hope this review has provided enough of a landscape overview to prompt further exploration of the utility of OR in this context. A complete database of the 1099 studies is provided as Additional file 2.

Income categories for countries were based on 2014 World Bank classifications, regardless of how a country may have been classified historically. It would have been difficult to track shifts in income classification for every country and every paper included in this review. Furthermore, we felt the interpretation would be simpler knowing that all studies related to a specific country (e.g. Brazil) were consistently counted towards its current income category (e.g. upper-middle) rather than split across multiple categories.

Our criteria for ‘impact’ when selecting case examples was that the study meaningfully informed a policy decision or the recommendations were implemented in a real-world setting. We were unable to make any inferences about the magnitude of improvement in health that may result from these changes. Only Hutton et al. [38] presented estimates that 170 million children would be vaccinated for hepatitis B in China as a result of their model recommendations, preventing almost 8 million infections and 70,000 deaths, and saving the equivalent of $1.4 billion over the lifetime of these children.

A final limitation of this review was the restricted search for published literature alone. Those papers that did not describe a particular policy change could have indeed influenced decision-making after their publication. Future work could involve searching grey literature for case studies and policy documents suggesting that knowledge gained from OR was influential in decision-making processes. The lack of published evidence that OR is impacting policy change represents a major missed opportunity for the academic community to learn and better engage in impactful OR work. It has been mentioned that fora are needed where these findings can be discussed [219] and success stories of policy transfer shared with a broader community [14], if not in peer-reviewed literature, then elsewhere.

In general, scoping reviews take a considerable amount of time and skill. Balancing feasibility, breadth and comprehensiveness can be a challenge given available time, funding and resources [35, 37]. Although not explicitly tracked, we thought it would be informative to provide an estimate of the amount of time that it took to conduct our review. The most time intensive stages were stages 2 to 4 – designing the search, identifying and selecting studies and charting data. Stage 2 was conducted over a period of approximately 4 months by one author on a near full-time basis (estimated 500 person-hours), and stages 3 and 4 were carried out by four co-authors over a period of approximately 8 months, all on a part-time basis (estimated 340 person-hours). This is consistent with the findings of Pham et al. [36], who reported scoping reviews have taken anywhere from 2 weeks to 20 months to complete.

Global overview and global health application areas
Despite these limitations and challenges, this scoping review, consisting of 1099 studies, is to our knowledge the most comprehensive review of OR in global health to
date. Our overview highlighted that low-income countries are less frequently studied using OR compared to middle-income countries, a trend that does not seem to be improving with time. Furthermore, a large proportion of healthcare-related OR in LMICs has focused on just six middle-income countries. If population is an appropriate yardstick for research focus, then perhaps this representation is reasonable; however, the disparity between volume of literature and number of countries in each income category is much more pronounced. That being said, 84 LMICs around the globe have been the focus of at least one OR study since 2000; hopefully, increased global coverage will continue.

Although the aggregate data did not show that any particular OR method was dominant, we found that certain types of research questions were more amenable to specific OR methods than others (e.g. local and national-level health systems problems were commonly studied with simulation or optimisation methods). This highlights the importance of a collaborative and interdisciplinary approach to applying OR in global health, such that those with modelling expertise in specific methods can apply their expertise where it can make the most impact.

We found that the majority of OR literature explores clinical medicine and public health issues at a national level, and that, although very helpful for exploring the impact of interventions on a macro scale or adding to discussions on global priority-setting, fewer studies were targeted at the regional or global level. Since OR models tend to describe the dynamics and interdependencies of actual systems, it likely gets more difficult to develop accurate models as complexity increases (i.e. from local or national systems to regional or global systems). OR models are also highly dependent on input data, which is likely easier to obtain at the local and/or national level. Studies targeted at several countries or a whole region have themselves cautioned that more specific country-level analyses with more representative data are needed for country-level decision-making, which is perhaps why few studies are targeted at these levels [135, 193].

One area of global health that OR has made a unique contribution to is the analysis of new health innovations. This small subset of studies highlights the value of OR for analysing global health interventions that cannot yet be trialled or implemented on the ground because the scientific breakthroughs have yet to be achieved. Understanding the potential impact or possible implementation challenges of new innovations is important to their successful roll-out when they do become available. OR can also help highlight important design criteria targets for the development of new innovations, in terms of both cost and minimum levels of efficacy or specificity required to achieve desired outcomes.

Infectious diseases (e.g. HIV/AIDS, malaria, TB) continue to be a major focus of OR globally; however, there has been an increase in the number of OR studies about non-communicable diseases over the past 5 years. Neglected areas representing an opportunity for future OR include analyses focused on low- and lower-middle income countries, non-communicable diseases (particularly mental health), and medical equipment and technology planning.

Additional study characteristics that could have been analysed include the funding sources, the academic institutions of the lead investigators and the quality of the studies themselves. Funding sources have been identified as a potential external influence on both research and policy agendas, but in some cases resources dedicated to an OR study can lead to positive change. For example, two studies from this review [43, 223] were funded by the Brazilian Ministry of Health [223], indicating interest on the part of the government to use OR as a tool to answer a key health systems-related questions. Exploring funding sources in more detail could be an area of future consideration. The quality of the studies themselves could also be highly relevant to successful research uptake, but we did not undertake critical appraisal for this review as quality assessment does not typically form part of the scoping study remit [34]. Others have reported on the quality of simulation models in healthcare by applying strict quality criteria during the review process [18].

Health equity: an opportunity for future OR

The healthcare equity-themed studies featured in this review demonstrate the utility of OR for informing equitable health policy decision-making in low-resource settings. These studies, however, represented a relatively minor proportion (4%) of all global health-related OR in the time period studied. Some have argued that a major shortcoming of the Millennium Development Goals was a failure to address equity [6], and that “looking forward, equity analyses and actions need to be an integral part of programme strategies rather than an afterthought” [7]. We believe a huge opportunity exists to apply the tools and techniques of OR to study health equity in the post-2015 era.

First, OR is extremely versatile in how the concept of health equity can be operationalised. The examples in this review demonstrate a variety of different ways to quantify equity - from measured disparities in specific health indicators to parameterised model variables. Although beyond the scope of this review, these principles can be used to explore the broader social determinants of health as well. As no single measure is sufficient to assess inequities, those applying OR to health equity...
could benefit from integrating established health equity frameworks into their approach (e.g. the PROGRESS [224, 225] and PROGRESS-Plus [226] frameworks) to help ensure the explicit consideration of important equity factors in the design of OR models and analyses. Second, OR allows for the comparison of different equity goals (e.g. using different ethical principles or comparing efficiency versus equity), often within the same modeling framework. For example, a utilitarian perspective aims to maximise overall societal benefit, whereas an egalitarian approach would strive to achieve equal distribution of, or access to, resources for every person [183]. OR allows for a more systematic analysis of the trade-offs and consequences of viewing equity from these different perspectives. Third, OR models can study the effect that different policies or decisions might have on marginalised populations without the ethical implications of a real-world study. Arguments could be made that, to achieve health equity, certain groups should be valued over others; for example, perhaps high-risk groups or the least advantaged should be prioritised, rather than treat all cases alike regardless of social standing. OR can aid in testing such sensitive policy hypotheses a priori without unintentional consequences.

OR can be applied at national and sub-national levels, across different socioeconomic groups and marginalised populations, and through different ethical lenses, in order to inform interventions and health policy decisions that will promote better equity in health going forward. We hope the equity-themed literature highlighted in this review can help open up important discussions about how best to model and analyse systemic disparities in health for all people worldwide.

**OR impact: recommendations for bridging the gap between OR and policy or practice**

Studies describing OR implementation or impact represent a small proportion of the literature reviewed – there is still a far way to go for OR to reach its full potential in global health. Our finding that few papers present details of implementation or impact is consistent with the experience of others who have reviewed OR in developing countries [10, 11, 23, 24]; for example, Datta [10] reported that less than 5% of studies reviewed discussed implementation. From the numerous studies included in this review that did not appear to have any influence on policy or decision-making, several persistent challenges emerged as common themes, including lack of local or expert stakeholder engagement in model conception and design, challenges in acquiring reliable and representative data, and a lack of communication strategy beyond the journal publication.

The lack of appropriate packaging of research findings or exclusive dissemination within academic circles was also found by others to be barriers to research uptake in LMICs [219, 227]. In recent years, several theories, frameworks and practical handbooks or ‘toolkits’ have been developed by agencies such as the Overseas Development Institute [228–230], the International Development Research Council [231], the WHO [232], and the Institute of Development Studies [233], to help guide and make more effective the translation of research into policy. Specifically, there is a focus in this literature on the effective communication of research findings, which extends beyond just communication products (e.g. policy brief, stories of change, etc.) to a whole body of research on knowledge sharing, knowledge transfer and knowledge translation. The use of packaging and language are more appropriate and targeted towards implementation can help enhance the impact of OR.

Yet, there have been many success stories of global health research effectively bridging the research-policy gap [13, 234]. For example, Zachariah et al. [13] identified several impactful operational research studies that had implications for policy and practice; however, all of these studies were field studies that did not involve modelling and thus did not meet the inclusion criteria for this review. Additional guidance to be gleaned from these studies for the OR modelling community include (1) the generation of research questions from within existing programs, which are focused and of simple design; (2) working with partners to ensure that sufficient resources (human and financial) are available for an engaged and motivated research process that extends beyond models and analyses; (3) setting realistic expectations of research impact; (4) investing in long-term research and policymaker relationships; and (5) helping build capacity of end-users to use research to demand policy change [13, 234].

Promisingly, within the OR community, there is a growing movement towards impact-driven research and publication. The “Doing Good with Good OR” paper series and research award, offered by the Institute for Operations Research and the Management Sciences, and the “OR in Development” prize, offered by the International Federation of Operational Research Societies, are efforts to recognise OR for the impact of the analysis, in addition to its analytical rigor. In general, there is a need for incentivising the engagement of researchers in problems that are relevant and timely to important policy issues [219]. Hopefully, these efforts, paired with efforts within developing countries to increase end-user capacity to use OR [11, 25] will help bridge the gap between OR and impact in LMICs.

**Conclusion**

There is a tremendous opportunity for OR researchers and global health practitioners alike to continue to apply
OR in global health, particularly in areas where such studies may currently be lacking. We hope the findings of this scoping review, which represents the most comprehensive compilation of OR literature in global health to date, are of interest to a wide-ranging group of stakeholders engaged in global health policy and practice. For government bodies and administrators of health programs and services, we hope to have showcased the utility of the OR approach in modelling policy and programme changes to improve efficiency, particularly when resources are limited. We also hope funders of international development research see value in allocating funding to operations research within broader global health programs. We hope those currently engaged in or can benefit from the impactful studies highlighted in this review, and we encourage them to share the impact of their work more broadly so that others can learn from challenges and successes.

Endnotes

1 The optional ‘Consultation Exercise’ of the framework was not conducted.
2 Individualised search strategies were based on whether the database was indexed by subject headings, controlled vocabulary or keywords.
3 World Bank classification as of July 1, 2014, not the year the study was published. Note that some countries may have shifted categories since 2000.
4 Based on World Bank country and population listings [235]. There were 136 low- and middle-income countries as of 2014.

Additional files

Additional file 1: Search strategies for Scopus, Compendex, Inspec and HealthStar databases. Description: Tables containing details of custom systematic search strategies for the Scopus, Compendex, Inspec and HealthStar databases. (DOCX 96 kb)

Additional file 2: Database of references included in review. Description: An Excel database of the 1099 references included in the global overview of this review paper, including columns for Authors, Title, Journal and/or Conference and/or Book Title, Year, Volume, Pages, Conference location and/or Place Published, and Abstract. (XLTX 893 kb)

Abbreviations

aNAAT: automated nucleic amplification test; ARV: anti-retroviral; DES: discrete-event simulation; DDS: decision support system; EPI: Expanded Programme on Immunization; LMICs: low- and middle-income countries; OR: operations research; TB: tuberculosis.

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Availability of data and materials

All data generated or analysed during this study are included in this published article [and its supplementary information files].

Authors’ contributions

BDB conceived the study idea, designed the systematic search, conducted the initial screen of search results, reviewed papers for the second screen of search results, categorised papers, contributed to the interpretation of data, and drafted the first manuscript. TJ, AT-V, BK reviewed papers for the second screen of search results and categorised papers, and TJ contributed to writing the paper. TJ, TCYC and Y-LC contributed to the study design and interpretation of data, and critically revised the draft. AT-V and BK provided comments on the draft. All authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

Consent for publication

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Ethics approval and consent to participate

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Appendix B

Random Variables in the Discrete-event Simulation of the OxOpt Model

This appendix provides supplementary details about the random variables and probability distributions used in the SIM component of the OxOpt model (see Chapters 5 and 7 and Figs. 5.1 and 7.1).

B.1 Random Variables of the Health Facility System Model (HFSM):

B.1.1 Patient arrivals

*Model parameter:* $\lambda_i$ (for HF $i$, $i = 1, \ldots, n$)

In health services-related DES models, patient admission rates have to be translated into ‘events’; in this case patient arrivals. These random, unscheduled events are often assumed to follow a Poisson process\(^1\) [4, 126, 143], which naturally arises in cases when knowledge that an arrival has or has not occurred gives no additional information about the time of the next arrival – a phenomenon known as the ‘memoryless’ property [143]. The Poisson process is characterized by a rate parameter, $\lambda$, which is the expected number of ‘events’ (or arrivals) that occur per unit time; for example, $\lambda$ patients per year.

By virtue of the fact that these random unscheduled patient arrivals arise from a Poisson process, the corresponding inter-arrival times of these visits are exponentially distributed. If $\lambda$ is in units of patients per year, the exponential distribution has a mean of $\mu = 1/\lambda$ years and a probability density function (PDF) represented by the following equation:

$$f(t) = \lambda e^{-\lambda t}; t \geq 0$$  \hspace{1cm} (B.1)

By sampling inter-arrival times from this distribution, a DES model can generate a sequence of random patient arrivals, which, on average, will be $1/\lambda$ years apart and will result in $\lambda$ patients per year.
In the OxOpt model, the user-defined $\lambda_i$ for each health facility is combined with the seasonality factors (i.e., beginning and end of the high season, denoted by $\tau F_i$ and $\tau L_i$, pitch of the high season ramp-up, $z_i$, and proportion of admissions in high season, $\eta_i$ - see section 7.3 for parameter definitions) to provide season-appropriate patient admission rates. These rates are converted into mean inter-arrival times (in hours) for the random sampling of inter-arrival times using Equation B.1. The result is that $(1 - \eta_i)\lambda_i$ and $\eta_i\lambda_i$ patients, on average, arrive during the low and high seasons, respectively for health facility $i$.

### B.1.2 Flow rate

*Model parameter: $F$, not currently editable by user*

Rather than assume a constant flow rate for all patients, this variable is randomly assigned to individual hypoxaemic patients in the simulation. The typical range of prescribed flow rates for children under five is between 0.5 and 3 L/min [61].

In controlled studies to determine effective and safe modes of oxygen delivery to children suffering from hypoxaemia (i.e., using nasal prongs, nasal catheter, or nasopharyngeal catheter) [92,93,113,140], average flow rates required to achieve greater than 90% $\text{SpO}_2$ ranged from 0.62 ± 0.54 L/min [140] to 0.98 ± 0.82 [92], but no distribution of these sample populations were provided.

To reflect the available evidence in the literature, variability in prescribed flow rates is modelled using a modified discrete Poisson distribution as described by Equation B.2. The probability density function is shown in Fig. B.1. The random variable, $F$, has a mean of $\rho = 1$ L/min, is lower bounded by 0.5 L/min, and is discrete in increments of 0.5 L/min (due to limitations of oxygen flow splitting technology [86]). As shown in Fig. B.1, most patients would receive 0.5 L/min or 1 L/min; higher flow rates are possible for rare severe cases. It is assumed that this distribution does not change for the peak season.

$$F = \frac{f + 1}{2}; \text{where } f \sim \text{Po}(\rho = 1)$$

### B.1.3 Length of stay (treatment duration)

*Model parameter: $T$, not currently editable by user*

Another factor affecting oxygen demand is oxygen treatment duration. In the OxOpt model, treatment duration is likened to hospital length of stay. The Weibull distribution is widely used in health services DES models for describing the distribution of ‘length of stay’ [83]. The PDF of the Weibull distribution is given by the following equation:

$$f(t) = \frac{\alpha}{\mu} \left(\frac{t - \delta}{\mu}\right)^{\alpha - 1} e^{-\left(\frac{t - \delta}{\mu}\right)^{\alpha}}; t \geq \delta, \delta \geq 0$$

where $\mu$ is the average stay duration and $\alpha$ describes whether the probability of leaving the hospital is increasing ($\alpha > 1$) or decreasing ($\alpha < 1$) during the stay; $\alpha = 1$ means the instantaneous probability

---

1Three mathematical assumptions must be satisfied in order for an arrival process to be Poisson; 1) arrivals can only occur one-at-a-time, 2) arrival patterns must not change as the day progresses, and 3) arrivals in disjoint portions of the day must be statistically independent of each other [143].
Appendix B. Random Variables in the Discrete-event Simulation of the OxOpt Model

Figure B.1: Probability density function for $F$, the random variable for patient flow rate. Distribution is based on a modified discrete Poisson distribution. The resulting random variable, $F$, has a mean of $\rho = 1$ L/min, is lower bounded by 0.5 L/min, and is discrete in increments of 0.5 L/min.

of leaving does not depend on the length of stay. If the minimum LOS can approach 0, $\delta$ can be assumed to be 0; otherwise $\delta \neq 0$ is used when the minimum LOS is 1 or more days [116].

If it can be assumed that $\alpha = 1$ and $\delta = 0$, this distribution is reduced to an exponential distribution with mean $\mu$, as follows [116]:

$$f(t) = \frac{1}{\mu}e^{-\frac{t}{\mu}}; t \geq 0 \quad (B.4)$$

For the random variable describing treatment duration in the OxOpt model, the simplified Weibull distribution as given by Equation B.4 is used, with a mean of $\mu = 3.5$ days. This value for $\mu$ was based on evidence in the literature. For example, a study from The Gambia about oxygen delivery methods reported average oxygen treatment duration to be $3.65 \pm 2.92$ days for a study population of 59 children using nasal prongs [140]. A study in Papua New Guinea reported that median duration of hypoxaemia after admission was 4 days (2 - 8 days). In a clinical guideline document, the WHO reports that in general, treatment duration can be expected to range from 2 to 5 days [147]. Since distributions for these data were not given, a benefit of using an exponential distribution to describe treatment duration is that only one parameter - the mean - needs to be chosen.

B.1.4 Time between power interruptions

Model parameter: $\psi F_i$ (when $\Psi_i = 0$, for HF $i, i = 1, \ldots, n$)

For health facilities that experience random power interruptions, the time between power interruptions is modelled as a normally distributed random variable, with a PDF as follows:

$$f(t) = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(t-\mu)^2}{2\sigma^2}} \quad (B.5)$$
where $\mu$ is the mean and $\sigma^2$ is the variance.

In the OxOpt model, the mean is a user-defined, health facility-specific parameter $\psi F_i$ (in hours). The standard deviation is set to $\sigma = 0.1\psi F_i$ (i.e., ±10% of the mean, but this could be changed to suit the specific location if data are available).

### B.1.5 Duration of power interruptions

*Model parameter: $\psi D_i$ (when $\Psi_i = 0$, for HF $i, i = 1, \ldots, n$)*

For health facilities that experience random power interruptions, the duration of power interruptions is modelled as a normally distributed random variable (Equation B.5) with a user-defined, health facility-specific mean of $\psi D_i$ (hours). The standard deviation is set to $\sigma = 0.2\psi D_i$ (i.e., ±20% of the mean, but this could be changed to suit the specific location if data are available).

### B.2 Random Variables of the Technology System Model (TSM):

The Concentrator Module of the Technology Systems Model (TSM) simulates the frequency of oxygen concentrator repairs and equipment downtime at the health facility-level. Probability distributions for time between failures and time to complete a repair (i.e., equipment downtime) were determined using data from the study presented in section 3.1 and [18] using Stat::Fit (Geer Mountain Software Corp, South Kent, CT). This analysis is based on 33 non-preventive maintenance related repairs across 27 concentrators between 2006 and 2013. Any repair whose work order was opened and closed on the same day was assumed to have a downtime of two hours (i.e., the minimum labour time allotted to complete a repair).

#### B.2.1 Time between failures

Time between failures (hours) was log-normally distributed, with $\mu = 9.4$ and $\sigma = 0.8$, which has a mean of about 16,500 hours (or 685 days). The PDF for the lognormal distribution is as follows:

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} e^{-\frac{(\ln t - \mu)^2}{2\sigma^2}}$$  \hspace{1cm} (B.6)

The probability density of the raw data and fitted distribution for time between repairs is shown in Fig. B.2A.

#### B.2.2 Time to complete a repair

Time to complete a repair (hours), or equipment downtime, was exponentially distributed (see Equation B.4), with $\mu = 1810$, although this was not as strong of a fit due to a couple of outliers in the > 9000 hours range, as shown in Fig. B.2B.
Appendix B. Random Variables in the Discrete-event Simulation of the OxOpt Model

Figure B.2: Raw data and fitted distributions for random variables corresponding to oxygen concentrator repairs. (A) Time between repairs is log-normally distributed (with $\mu = 9.4$, $\sigma = 0.8$, and mean of about 16,500); (B) time to complete repairs is exponentially distributed (with $\mu = 1810$).
Appendix C

Genetic Algorithm Parameter Selection: Design of Experiment

C.1 Introduction and Methods

For the OxOpt model, an orthogonal array design of experiment (DOE) was chosen to determine appropriate settings for four configurable genetic algorithm parameters: population size, elite count, crossover fraction, and number of stall generations (‘stall count’). A total of 16 experiments were conducted to test each factor at four different levels such that for any pair of parameters, all combinations of factor levels occur and they occur an equal number of times (see Fig. C.1).

The experiment was conducted for a hypothetical scenario consisting of 5 health facilities with patient admissions ranging from 250 to 2000 annually (other scenario characteristics are given in Table 7.3). The outcomes of interest were the objective function value (i.e., total system cost) as a performance measure and computation time as an efficiency measure. Each case was run three times and averaged due to the stochastic nature of the SIM model and random behaviour of the GA.

Population size was tested as a multiple of the number of decision variables, which is a function of the number of health facilities being modelled (in the case of these experiments, five health facilities result in ten decision variables). Since the OxOpt model is scalable and can analyze more than five health facilities, the number of decision variables also scales. In the following section, additional review of the literature was done to explore the effect of population size on GA performance and how to optimally choose an appropriate population size.

C.1.1 The effect of population size: Additional insight from the literature

The primary tradeoff with population size is that small population sizes run the risk of insufficiently covering the solution space leading to poor solutions, and large population sizes could lead to unnecessary computation time and reduce the practicality of the GA approach for real-world problems [78, 106, 109, 112]. Theoretically, the optimal population size increases exponentially with increasing problem size [54, 55], but this has since been considered as pessimistic in light of empirical experiments [3, 109].

In the literature, experimental investigations into the influence of population size for specific problems (e.g., biological models [112], electromagnetics [60], control systems [3, 99] and other general optimiza-
tion problems [57]) have shown that increasing the population size improves the objective function result to a certain point, but that further increases in population size do not necessarily lead to better objection function values, and serve only to increase processing time. Others have attempted to specify generalizable ‘rules of thumb’ based on certain problem properties. For example, Alander [3] suggests a population size between \( n \) and \( 2n \), where \( n \) is the length of the solution vector [3]. Reeves [109] proposes choosing a minimum population size such that every possible point in the search space is ‘reachable’ from the initial population by crossover only. Theoretical curves are provided for finding the minimum population size given different solution vector lengths (\( n \)) and the number of possible assignments for each variable [109]. These findings will be taken into account when choosing an appropriate population size for model scenarios consisting of more than 5 health facilities.

C.2 Results

Objective function values (i.e., total system cost) and computation time (hours) for each experiment are summarized in Fig. C.1. Figures C.2 to C.5 show the effect of increasing levels of each parameter on the objective function value and on processing time, along with the mean values across the four experiments at each level.

Increasing population size and stall generation count are correlated with increased processing time, with the longest recorded time being when population size was 40 and stall count was 30 (experiment 13) - see Figs. C.2 and C.5. These two parameters did not have as strong of an effect on the objective function value, but did show slightly lower total cost values at lower parameter levels. On average, the lowest cost was found when population size was 10 and stall count was 10.

The best average cost results for elite count and crossover fraction were achieved at mid-range values (0.2 - 0.3 and 0.6, respectively), although ‘optimal’ values (~$55,000) were achieved at all three of the lowest levels for both parameters when population size was 10 (Figs. C.3 and C.4). Comparing the 0.2 and 0.3 levels for elite count when experiments at high stall count and population size levels are excluded (based on the finding above that lower values for these parameters are better), an elite count of 0.2 appears to be a better option than 0.3, which has an average total cost about 3% higher. Processing time was highly variable for these two parameters and dominated by the population size and/or stall count for each respective experiment.

Based on these results, low population size and stall count values are sufficient for achieving both low objective function values and processing times. The choice of elite count and crossover fraction was less clear, but chosen to be 0.2 and 0.6 respectively to achieve the best balance between objective function value and processing time. Final parameter value selections are summarized in Table 7.4.

Consistent with the literature presented in section C.1.1, better objective function values were not necessarily achieved by increasing the population size. However, these results might only be valid for scenarios with 5 health facilities. For all future scenarios larger than 5 health facilities, population size will be scaled appropriately (i.e., by consulting the curves presented in Reeves [109] and/or applying the rule that population size should be between \( n \) and \( 2n \) [3]) to cover a sufficiently large sample of the solution space. For example, a problem with 10 facilities (20 decision variables) should have a population between 20 and 40 according to Alander [3], or between 15 and 50 according to Reeves [109]. The Gambia case study of Chapter 8 with 11 facilities should have between 15 and 52, according to Reeves [109].
## Appendix C. Genetic Algorithm Parameter Selection: Design of Experiment

### Table C.1: GA Parameter Selection Experimental Setup and Results

<table>
<thead>
<tr>
<th>Exp. No.</th>
<th>Pop Size $^a$</th>
<th>Elite Count $^b$</th>
<th>Crossover Fraction</th>
<th>Stall Count</th>
<th>Objective Value ($)$</th>
<th>Processing Time (h)</th>
<th>Processing Time (% of longest time)</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>10</td>
<td>0.2</td>
<td>10</td>
<td>$55,114$</td>
<td>37</td>
<td>10.1 (0.3) 14.8%</td>
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<tr>
<td>2</td>
<td>10</td>
<td>20</td>
<td>0.4</td>
<td>20</td>
<td>$55,129$</td>
<td>29</td>
<td>15.6 (1.7) 22.7%</td>
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<tr>
<td>3</td>
<td>10</td>
<td>30</td>
<td>0.6</td>
<td>30</td>
<td>$55,121$</td>
<td>13</td>
<td>17.0 (0.5) 24.8%</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>40</td>
<td>0.8</td>
<td>40</td>
<td>$58,425$</td>
<td>1,538</td>
<td>18.5 (0.8) 27.0%</td>
</tr>
<tr>
<td>5</td>
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<td>10</td>
<td>0.4</td>
<td>30</td>
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<td>5,803</td>
<td>49.2 (2.7) 71.8%</td>
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<tr>
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<td>20</td>
<td>0.6</td>
<td>40</td>
<td>$61,327$</td>
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<td>45.1 (9.3) 65.9%</td>
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<tr>
<td>7</td>
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<td>30</td>
<td>0.8</td>
<td>10</td>
<td>$59,969$</td>
<td>1,038</td>
<td>26.1 (0.5) 38.1%</td>
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<tr>
<td>8</td>
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<td>40</td>
<td>0.2</td>
<td>20</td>
<td>$60,810$</td>
<td>8</td>
<td>28.1 (3.3) 41.0%</td>
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<tr>
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<td>10</td>
<td>0.6</td>
<td>10</td>
<td>$58,633$</td>
<td>2,488</td>
<td>41.9 (10.6) 61.2%</td>
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<tr>
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<td>20</td>
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<td>30</td>
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<td>$60,080$</td>
<td>1,055</td>
<td>42.0 (5.2) 61.4%</td>
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<tr>
<td>12</td>
<td>30</td>
<td>40</td>
<td>0.4</td>
<td>40</td>
<td>$58,373$</td>
<td>152</td>
<td>55.4 (3.3) 80.9%</td>
</tr>
<tr>
<td>13</td>
<td>40</td>
<td>10</td>
<td>0.8</td>
<td>30</td>
<td>$59,588$</td>
<td>1,848</td>
<td>68.5 (10.6) 100.0%</td>
</tr>
<tr>
<td>14</td>
<td>40</td>
<td>20</td>
<td>0.2</td>
<td>40</td>
<td>$59,839$</td>
<td>2,104</td>
<td>59.5 (5.3) 87.0%</td>
</tr>
<tr>
<td>15</td>
<td>40</td>
<td>30</td>
<td>0.4</td>
<td>10</td>
<td>$58,389$</td>
<td>184</td>
<td>51.6 (8.2) 75.3%</td>
</tr>
<tr>
<td>16</td>
<td>40</td>
<td>40</td>
<td>0.6</td>
<td>20</td>
<td>$58,834$</td>
<td>505</td>
<td>63.0 (5.8) 92.0%</td>
</tr>
</tbody>
</table>

$^a$ 1, 2, 3 and 4 x number of decision variables (which is 10 for this experiment of 5 health facilities)

$^b$ Percentage of population size

Figure C.1: GA Parameter Selection Experimental Setup and Results. Objective function value and processing time presented as mean and standard deviation across 3 trials for each experiment. Processing time also presented as per cent of longest processing time (exp. 13).
Figure C.2: **Effect of population size on genetic algorithm outcomes.** (A) Objective function value and (B) processing time with increasing population size. Processing time presented as per cent of longest processing time. Mean across 4 experiments at each population size level indicated with black squares and trendline.
Figure C.3: Effect of elite count on genetic algorithm outcomes. (A) Objective function value and (B) processing time with increasing elite count. Processing time presented as per cent of longest processing time. Mean across 4 experiments at each elite count level indicated with black squares and trendline.
Figure C.4: **Effect of crossover fraction on genetic algorithm outcomes.** (A) Objective function value and (B) processing time with increasing crossover fraction. Processing time presented as per cent of longest processing time. Mean across 4 experiments at each crossover fraction level indicated with black squares and trendline.
Figure C.5: **Effect of number of stall generations on genetic algorithm outcomes.** (A) Objective function value and (B) processing time with increasing number of stall generations. Processing time presented as per cent of longest processing time. Mean across 4 experiments at each stall generation level indicated with black squares and trendline.
Appendix D

Genetic Algorithm Iteration Count and Archive Size Experiments

D.1 Iteration Count Experiment

D.1.1 Introduction and methods

An experiment was designed to determine the minimum number of simulation iterations required to achieve statistical equivalence to a higher (more computationally intensive) number of iterations in order to reduce simulation computation time. The same hypothetical scenario used for the genetic algorithm parameter selection experiments was used (see section 7.6.3 and Table 7.3 for scenario characteristics). Five randomly generated solution vectors formed the basis for five separate ‘trials’ (see Fig. D.1).

For each trial, five hundred iterations were simulated and results obtained for 9 different output measures (total cost, satisfied demand, unsatisfied demand, unmet proportion of demand, number of repairs, number of patients treated, partially treated, and untreated, and lives saved). Averages of these measures across all 500 iterations were treated as the ‘true’ means. From these iterations, 10 groupings of 3, 5, 10, 25 and 50 iterations were formed and averaged; these results were then compared to the ‘true’ mean and to results at other iteration counts using a student t-test.

<table>
<thead>
<tr>
<th>Random Trial</th>
<th>Number of Concentrators</th>
<th>Alternative Energy Decision</th>
<th>Trial Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HF1</td>
<td>HF2</td>
<td>HF3</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>9</td>
<td>4</td>
</tr>
</tbody>
</table>

Figure D.1: Five randomly generated solution vectors (trials) for iteration count experiment. Solution vector values for number of concentrators and binary alternative energy decision for each of five health facilities.
D.1.2 Results and discussion

Results for all trials and output metrics are summarized in Figs. D.2 and D.3. There was less than a 0.5% difference in total cost (the key objective function measure) across all trials when using 5 iterations compared with the ‘true’ mean. For all other output metrics, maximum percent difference across all five trials ranged from 0.6% to 9.3%.

Across all 5 scenarios and 9 different output measures, there was no significant difference between the results obtained for simulations with 5 iterations versus those with 10, 25 or 50 iterations ($p > 0.05$) (Fig. D.4). When considering using as few as 3 iterations compared to 25 or 50, only trial 5 resulted in significant differences for two output measures (total cost and number of repairs). Total cost in this case however was only 0.06% different than the mean calculated with 500 iterations. This scenario had the highest number of concentrators of all 5 trials, perhaps leading to higher variability in total cost and number of repairs.

Based on this experiment, it was concluded that 3 to 5 simulation iterations would be sufficient when processing the SIM model embedded within the OxOpt model. An iteration count of 5 offers more confidence that the results will be statistically significant, however if processing time is highly limited, 3 iterations could be used.
### Output metric: Total cost ($USD)

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th>Trial 2</th>
<th>Trial 3</th>
<th>Trial 4</th>
<th>Trial 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>28,051</td>
<td>368</td>
<td>60,130</td>
<td>330</td>
<td>77,381</td>
</tr>
<tr>
<td></td>
<td>$1,123</td>
<td>$178,655</td>
<td>$871</td>
<td>$89,467</td>
<td>$1,025</td>
</tr>
<tr>
<td>5</td>
<td>28,089</td>
<td>370</td>
<td>60,163</td>
<td>330</td>
<td>77,377</td>
</tr>
<tr>
<td></td>
<td>$1,124</td>
<td>$178,556</td>
<td>$884</td>
<td>$89,692</td>
<td>$1,081</td>
</tr>
<tr>
<td>10</td>
<td>28,109</td>
<td>380</td>
<td>60,163</td>
<td>347</td>
<td>77,332</td>
</tr>
<tr>
<td></td>
<td>$1,125</td>
<td>$178,655</td>
<td>$906</td>
<td>$89,723</td>
<td>$1,259</td>
</tr>
<tr>
<td>25</td>
<td>28,128</td>
<td>365</td>
<td>60,192</td>
<td>372</td>
<td>77,386</td>
</tr>
<tr>
<td></td>
<td>$1,129</td>
<td>$178,767</td>
<td>$907</td>
<td>$90,070</td>
<td>$1,267</td>
</tr>
<tr>
<td>50</td>
<td>28,115</td>
<td>374</td>
<td>60,208</td>
<td>361</td>
<td>77,379</td>
</tr>
<tr>
<td></td>
<td>$1,125</td>
<td>$178,820</td>
<td>$886</td>
<td>$90,040</td>
<td>$1,293</td>
</tr>
</tbody>
</table>

| % diff (5 & 50)| 0.09%   | 0.07%   | 0.00%   | 0.15%   | 0.39%   |

### Output metric: Satisfied demand (L)

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th>Trial 2</th>
<th>Trial 3</th>
<th>Trial 4</th>
<th>Trial 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>21,611,366</td>
<td>21,714,224</td>
<td>21,914,911</td>
<td>25</td>
<td>18,419,771</td>
</tr>
<tr>
<td></td>
<td>28,109</td>
<td>28,089</td>
<td>28,163</td>
<td>28,109</td>
<td>28,089</td>
</tr>
<tr>
<td></td>
<td>54.2%</td>
<td>54.0%</td>
<td>54.2%</td>
<td>54.8%</td>
<td>54.2%</td>
</tr>
<tr>
<td></td>
<td>0.92%</td>
<td>0.92%</td>
<td>0.92%</td>
<td>0.92%</td>
<td>0.92%</td>
</tr>
</tbody>
</table>

| % diff (5 & 50)| 0.92%   | 0.62%   | 0.20%   | 0.17%   | 0.07%   |

### Output metric: Unsatisfied demand (L)

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th>Trial 2</th>
<th>Trial 3</th>
<th>Trial 4</th>
<th>Trial 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>904,233</td>
<td>857,472</td>
<td>853,751</td>
<td>925,605</td>
<td>1,076,629</td>
</tr>
<tr>
<td></td>
<td>1,234,562</td>
<td>1,213,192</td>
<td>1,126,442</td>
<td>1,101,645</td>
<td>348</td>
</tr>
<tr>
<td></td>
<td>9.0%</td>
<td>6.1%</td>
<td>6.1%</td>
<td>6.1%</td>
<td>3.46%</td>
</tr>
</tbody>
</table>

### Output metric: Unsatisfied proportion of demand

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th>Trial 2</th>
<th>Trial 3</th>
<th>Trial 4</th>
<th>Trial 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>13.0</td>
<td>4.1</td>
<td>19.5</td>
<td>9.5</td>
<td>41.8</td>
</tr>
<tr>
<td></td>
<td>18.5</td>
<td>14.6</td>
<td>14.2</td>
<td>14.3</td>
<td>14.0</td>
</tr>
<tr>
<td></td>
<td>13.5</td>
<td>15.5</td>
<td>16.9</td>
<td>15.9</td>
<td>16.0</td>
</tr>
<tr>
<td></td>
<td>16.6</td>
<td>17.1</td>
<td>19.7</td>
<td>19.7</td>
<td>19.8</td>
</tr>
<tr>
<td>% diff (5 &amp; 50)</td>
<td>69.8%</td>
<td>65.0%</td>
<td>67.5%</td>
<td>68.7%</td>
<td>72.7%</td>
</tr>
</tbody>
</table>

### Output metric: Number of concentrator repairs

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th>Trial 2</th>
<th>Trial 3</th>
<th>Trial 4</th>
<th>Trial 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>11.9</td>
<td>4.0</td>
<td>19.4</td>
<td>6.1</td>
<td>41.8</td>
</tr>
<tr>
<td></td>
<td>14.0</td>
<td>14.0</td>
<td>14.0</td>
<td>49.6</td>
<td>16.1</td>
</tr>
<tr>
<td></td>
<td>58.7</td>
<td>58.7</td>
<td>58.7</td>
<td>9.7%</td>
<td>9.7%</td>
</tr>
</tbody>
</table>

| % diff (5 & 50)| 7.36%   | 7.36%   | 7.36%   | 7.36%   | 7.36%   |

Figure D.2: Simulation results for iteration counts of 3, 5, 10, 25 and 50 (1 of 2). Mean and standard deviation (SD) across 10 samples at each iteration count level. Simulation metrics include: total cost ($USD), satisfied demand (L), unsatisfied demand (L), unsatisfied proportion of demand (%) and number of concentrator repairs. Percent difference between 5 iterations and 50 also shown.
### Appendix D. Genetic Algorithm Iteration Count and Archive Size Experiments

#### Output metric: Number of patients treated

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th></th>
<th>Trial 2</th>
<th></th>
<th>Trial 3</th>
<th></th>
<th>Trial 4</th>
<th></th>
<th>Trial 5</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>3</td>
<td>1131.4</td>
<td>82.2</td>
<td>4012.8</td>
<td>176.4</td>
<td>4873.1</td>
<td>99.9</td>
<td>3877.9</td>
<td>75.9</td>
<td>4874.0</td>
<td>107.9</td>
</tr>
<tr>
<td>5</td>
<td>1130.2</td>
<td>92.4</td>
<td>3998.5</td>
<td>199.0</td>
<td>4874.8</td>
<td>113.1</td>
<td>3877.3</td>
<td>65.8</td>
<td>4865.2</td>
<td>119.2</td>
</tr>
<tr>
<td>10</td>
<td>1147.2</td>
<td>91.1</td>
<td>4030.2</td>
<td>203.8</td>
<td>4873.5</td>
<td>113.1</td>
<td>3888.4</td>
<td>77.2</td>
<td>4870.8</td>
<td>114.5</td>
</tr>
<tr>
<td>25</td>
<td>1154.7</td>
<td>89.7</td>
<td>4037.4</td>
<td>197.4</td>
<td>4872.3</td>
<td>127.8</td>
<td>3884.5</td>
<td>76.8</td>
<td>4862.4</td>
<td>123.5</td>
</tr>
<tr>
<td>50</td>
<td>1149.6</td>
<td>85.0</td>
<td>4046.3</td>
<td>196.0</td>
<td>4866.1</td>
<td>128.3</td>
<td>3888.6</td>
<td>80.1</td>
<td>4870.8</td>
<td>117.5</td>
</tr>
<tr>
<td>500</td>
<td>1149.6</td>
<td>85.0</td>
<td>4046.3</td>
<td>196.0</td>
<td>4866.1</td>
<td>128.3</td>
<td>3888.6</td>
<td>80.1</td>
<td>4870.8</td>
<td>117.5</td>
</tr>
</tbody>
</table>

% diff (5 & 500): 1.69%  1.18%  0.21%  0.29%  0.11%

#### Output metric: Number of patients partially treated

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th></th>
<th>Trial 2</th>
<th></th>
<th>Trial 3</th>
<th></th>
<th>Trial 4</th>
<th></th>
<th>Trial 5</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>3</td>
<td>5227.8</td>
<td>270.5</td>
<td>3338.8</td>
<td>142.6</td>
<td>2090.6</td>
<td>106.3</td>
<td>3530.0</td>
<td>251.0</td>
<td>2203.0</td>
<td>103.9</td>
</tr>
<tr>
<td>5</td>
<td>5263.4</td>
<td>266.5</td>
<td>3348.3</td>
<td>173.4</td>
<td>2055.8</td>
<td>111.2</td>
<td>3532.9</td>
<td>227.3</td>
<td>2215.2</td>
<td>111.6</td>
</tr>
<tr>
<td>10</td>
<td>5284.4</td>
<td>305.9</td>
<td>3331.7</td>
<td>182.4</td>
<td>2057.4</td>
<td>126.3</td>
<td>3557.2</td>
<td>258.7</td>
<td>2209.5</td>
<td>108.9</td>
</tr>
<tr>
<td>25</td>
<td>5294.0</td>
<td>334.6</td>
<td>3331.4</td>
<td>185.9</td>
<td>2057.7</td>
<td>131.5</td>
<td>3511.2</td>
<td>315.5</td>
<td>2215.3</td>
<td>116.5</td>
</tr>
<tr>
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<td>5272.5</td>
<td>344.8</td>
<td>3330.4</td>
<td>186.2</td>
<td>2055.2</td>
<td>136.6</td>
<td>3522.2</td>
<td>300.2</td>
<td>2202.1</td>
<td>111.7</td>
</tr>
<tr>
<td>500</td>
<td>5272.5</td>
<td>345.8</td>
<td>3330.4</td>
<td>185.9</td>
<td>2055.2</td>
<td>137.2</td>
<td>3522.2</td>
<td>306.1</td>
<td>2202.1</td>
<td>113.1</td>
</tr>
</tbody>
</table>

% diff (5 & 500): 0.17%  0.54%  0.03%  0.31%  0.59%

#### Output metric: Number of patients untreated

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th></th>
<th>Trial 2</th>
<th></th>
<th>Trial 3</th>
<th></th>
<th>Trial 4</th>
<th></th>
<th>Trial 5</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>3</td>
<td>1800.6</td>
<td>315.7</td>
<td>612.2</td>
<td>141.3</td>
<td>1061.4</td>
<td>158.3</td>
<td>3580.0</td>
<td>267.9</td>
<td>687.5</td>
<td>15.1</td>
</tr>
<tr>
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<td>1888.3</td>
<td>324.3</td>
<td>609.7</td>
<td>165.1</td>
<td>1049.5</td>
<td>132.0</td>
<td>567.7</td>
<td>253.3</td>
<td>891.7</td>
<td>27.4</td>
</tr>
<tr>
<td>10</td>
<td>1536.1</td>
<td>345.8</td>
<td>595.3</td>
<td>165.9</td>
<td>1035.2</td>
<td>130.4</td>
<td>531.5</td>
<td>276.1</td>
<td>890.4</td>
<td>28.9</td>
</tr>
<tr>
<td>25</td>
<td>1518.4</td>
<td>373.0</td>
<td>594.3</td>
<td>175.0</td>
<td>1040.6</td>
<td>146.2</td>
<td>576.6</td>
<td>334.3</td>
<td>892.2</td>
<td>32.2</td>
</tr>
<tr>
<td>50</td>
<td>1543.7</td>
<td>385.6</td>
<td>585.1</td>
<td>171.8</td>
<td>1048.3</td>
<td>151.5</td>
<td>561.2</td>
<td>321.5</td>
<td>890.8</td>
<td>32.6</td>
</tr>
<tr>
<td>500</td>
<td>1543.7</td>
<td>385.7</td>
<td>585.1</td>
<td>174.0</td>
<td>1048.3</td>
<td>151.6</td>
<td>561.2</td>
<td>328.1</td>
<td>890.8</td>
<td>32.4</td>
</tr>
</tbody>
</table>

% diff (5 & 500): 2.92%  4.20%  0.23%  1.15%  0.10%

#### Output metric: Number of lives saved

<table>
<thead>
<tr>
<th>Iteration Count</th>
<th>Trial 1</th>
<th></th>
<th>Trial 2</th>
<th></th>
<th>Trial 3</th>
<th></th>
<th>Trial 4</th>
<th></th>
<th>Trial 5</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>3</td>
<td>68.2</td>
<td>3.4</td>
<td>101.1</td>
<td>2.8</td>
<td>104.1</td>
<td>2.1</td>
<td>100.5</td>
<td>2.9</td>
<td>105.7</td>
<td>1.2</td>
</tr>
<tr>
<td>5</td>
<td>68.9</td>
<td>3.5</td>
<td>100.9</td>
<td>2.9</td>
<td>104.3</td>
<td>2.1</td>
<td>100.5</td>
<td>2.5</td>
<td>105.6</td>
<td>1.4</td>
</tr>
<tr>
<td>10</td>
<td>69.0</td>
<td>3.8</td>
<td>101.4</td>
<td>3.0</td>
<td>104.3</td>
<td>2.1</td>
<td>101.0</td>
<td>3.0</td>
<td>105.7</td>
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<td>4.0</td>
<td>101.5</td>
<td>3.0</td>
<td>104.3</td>
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<td>100.5</td>
<td>3.5</td>
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<td>101.6</td>
<td>2.9</td>
<td>104.1</td>
<td>2.5</td>
<td>100.6</td>
<td>3.4</td>
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<td>100.6</td>
<td>3.5</td>
<td>105.6</td>
<td>1.5</td>
</tr>
</tbody>
</table>

% diff (5 & 500): 0.62%  0.66%  0.18%  0.10%  0.02%

Figure D.3: Simulation results for iteration counts of 3, 5, 10, 25 and 50 (2 of 2). Mean and standard deviation (SD) across 10 samples at each iteration count level. Simulation metrics include: number of patients treated, partially treated and untreated and number of lives saved. Percent difference between 5 iterations and 500 also shown.
**Appendix D. Genetic Algorithm Iteration Count and Archive Size Experiments**

### D.2 Archive Size Experiment

#### D.2.1 Introduction and methods

A sim-opt experiment was conducted to determine how many solution evaluations should be compiled in the GA solution archive before no added benefit is achieved by additional solution evaluations. Two scenarios consisting of five and six health facilities were used. For each scenario, the complete OxOpt sim-opt process was run using Objective 1 with GA solution archive sizes of 10, 25 and 50. If throughout GA processing the number of evaluations of any particular solution reached the archive size, the mean of the archived objection function values was henceforth used whenever the algorithm called for that solution to be evaluated in future generations. The outcomes of interest for this experiment were the objective function value (i.e., total system cost) as a performance measure and computation time as an efficiency measure. The number of generations to convergence, percent coverage of the solution space, and number of solutions in the archive reaching the archive size were also recorded. Each case was run

<table>
<thead>
<tr>
<th>Trial</th>
<th>Iteration count for student t-test comparison</th>
<th>Output Metric</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Cost</td>
<td>Satisfied Demand</td>
</tr>
<tr>
<td>1</td>
<td>3 and 5</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>3 and 10</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>3 and 25</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>3 and 50</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>5 and 10</td>
<td>0.80</td>
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<td>5 and 25</td>
<td>0.57</td>
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<td>5 and 50</td>
<td>0.69</td>
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<td></td>
<td>3 and 25</td>
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</tr>
<tr>
<td></td>
<td>3 and 50</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
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<td>0.99</td>
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<td></td>
<td>5 and 25</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>5 and 50</td>
<td>0.42</td>
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<td>3 and 5</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>3 and 10</td>
<td>0.76</td>
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<td></td>
<td>3 and 25</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>3 and 50</td>
<td>0.99</td>
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<td>3 and 5</td>
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</tr>
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<td></td>
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<td>0.53</td>
</tr>
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<td></td>
<td>3 and 50</td>
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<td></td>
<td>5 and 10</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>5 and 25</td>
<td>0.21</td>
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<td>5 and 50</td>
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</tr>
<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>5 and 25</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>5 and 50</td>
<td>0.14</td>
</tr>
</tbody>
</table>

*Figure D.4: Results for student t-tests comparing mean values obtained from different iteration counts for nine simulation output metrics.* Ten samples at each iteration count level are compared, with green shading indicating no significant difference (p > 0.05) and red shading indicating a significant difference (p < 0.05) between the means.
three times and averaged due to the stochastic nature of the SIM model and random behaviour of the GA.

### D.2.2 Results and discussion

It was found that archiving 10 solution evaluations in the GA solution archive saves considerably on processing time and still leads to optimal solutions (Fig. D.5). For both the 5- and 6-health facility scenarios, optimal objective function values using an archive size of 10 were less than 1% different compared to an archive size of 25, and less than 3% different compared to an archive size of 50. Yet, processing times were up to 1.7 and 2.0 times longer for archive sizes of 25 and 50, respectively (Fig. D.5). Although processing time increased with increased archive size, these variables did not vary directly with one another, and the slope of the relationship differed for the 5- and 6-health facility scenarios.

There was no significant difference ($p > 0.1$)\(^1\) in percent coverage of the solution space or number of generations to convergence when using an archive size of 10 versus 25 or 50 (Fig D.6).

It was also observed that with an archive size of 10, solutions are less likely to survive in the beginning only to get rejected later in the processing, as can happen when the archive size is bigger. Also, the algorithm typically does not waste time on bad solutions anyway; not many even get close to 25 in the archive, let alone 50 (Fig D.6). Even when archive size was set to 25 or 50, fewer than 10 individual solutions ever reached 10 evaluations (Fig D.6). There does not appear to be an advantage in building the archive to 25 or 50, which serves only to increase processing time for a few promising solutions.

Based on these results, an archive size of 10 will be used in all future case studies.

---

\(^1\) $p$-value for student t-test comparing percent coverage for 3 repetitions of the two scenarios at each archive size level.
### Appendix D. Genetic Algorithm Iteration Count and Archive Size Experiments

<table>
<thead>
<tr>
<th>Exp. No.</th>
<th>Parameters</th>
<th>Results</th>
<th>Objective Value ($)</th>
<th>Processing Time (h)</th>
<th>Processing Time (% of longest time)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. HCs</td>
<td>Archive Size</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
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<td>5</td>
<td>10</td>
<td>$34,939$</td>
<td>$36$</td>
<td>3.9</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>25</td>
<td>$34,724$</td>
<td>$436$</td>
<td>4.4</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>50</td>
<td>$35,869$</td>
<td>$1,230$</td>
<td>5.8</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>10</td>
<td>$43,475$</td>
<td>$2,660$</td>
<td>7.0</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>25</td>
<td>$43,441$</td>
<td>$1,402$</td>
<td>11.7</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>50</td>
<td>$42,648$</td>
<td>$1,204$</td>
<td>14.1</td>
</tr>
</tbody>
</table>

Figure D.5: Experimental results for genetic algorithm processing using different solution archive sizes (1 of 2). Objective function values and processing times (mean ± standard deviation (SD) across 3 repetitions) for 5- and 6-health-facility scenarios with archive sizes of 10, 25 and 50.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. HCs</td>
<td>Archive Size</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
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<td>5</td>
<td>10</td>
<td>14.7</td>
<td>3.3</td>
<td>1.3%</td>
<td>0.0%</td>
<td>2.3</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>25</td>
<td>11.7</td>
<td>0.9</td>
<td>1.4%</td>
<td>0.0%</td>
<td>1.3</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>50</td>
<td>15.0</td>
<td>3.7</td>
<td>1.4%</td>
<td>0.0%</td>
<td>0.3</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>10</td>
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<td>2.4</td>
<td>1.0%</td>
<td>0.1%</td>
<td>4.7</td>
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<tr>
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<td>6</td>
<td>25</td>
<td>13.7</td>
<td>2.4</td>
<td>1.0%</td>
<td>0.1%</td>
<td>3.7</td>
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<tr>
<td>6</td>
<td>6</td>
<td>50</td>
<td>15.0</td>
<td>0.8</td>
<td>1.1%</td>
<td>0.3%</td>
<td>1.3</td>
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</table>

Figure D.6: Experimental results for genetic algorithm processing using different solution archive sizes (2 of 2). Number of generations to convergence, percent coverage of the solution space, and number of solutions reaching the set archive size or more than 10 in the archive (mean ± standard deviation (SD) across 3 repetitions) for 5- and 6-health-facility scenarios with archive sizes of 10, 25 and 50.
Appendix E

Detailed $OxOpt$ Model Results for The Gambia Case Study

This appendix contains detailed model outputs and results not included in the main thesis text.
### Status Quo Scenario

<table>
<thead>
<tr>
<th>Hospitals</th>
<th>Health Centres</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean ± SD</strong></td>
<td><strong>Mean ± SD</strong></td>
</tr>
<tr>
<td>Total Cost:</td>
<td>$26,061 ± $1,111</td>
</tr>
<tr>
<td>Capital Cost:</td>
<td>$4,100 ± $0</td>
</tr>
<tr>
<td>Operating Cost:</td>
<td>$21,961 ± $1,111</td>
</tr>
<tr>
<td>% Satisfied Demand:</td>
<td>68.5% ± 2.3%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>32 ± 1</td>
</tr>
<tr>
<td>Treated:</td>
<td>412 ± 22</td>
</tr>
<tr>
<td>Untreated:</td>
<td>416 ± 25</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>3,386 ± 180</td>
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</tbody>
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### Simulated (ES 1: Minimum scenario)

<table>
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<th>Health Centres</th>
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</thead>
<tbody>
<tr>
<td><strong>Mean ± SD</strong></td>
<td><strong>Mean ± SD</strong></td>
</tr>
<tr>
<td>Total Cost:</td>
<td>$23,959 ± $319</td>
</tr>
<tr>
<td>Capital Cost:</td>
<td>$11,250 ± $0</td>
</tr>
<tr>
<td>Operating Cost:</td>
<td>$10,709 ± $319</td>
</tr>
<tr>
<td>% Satisfied Demand:</td>
<td>69.1% ± 3.9%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>41 ± 3</td>
</tr>
<tr>
<td>Treated:</td>
<td>664 ± 46</td>
</tr>
<tr>
<td>Partials:</td>
<td>313 ± 23</td>
</tr>
<tr>
<td>Untreated:</td>
<td>185 ± 54</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>4,040 ± 294</td>
</tr>
</tbody>
</table>

### Optimized (ES 2: 80% demand satisfied for hospitals and health centers)

<table>
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<tr>
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</thead>
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<td><strong>Mean ± SD</strong></td>
<td><strong>Mean ± SD</strong></td>
</tr>
<tr>
<td>Total Cost:</td>
<td>$4,321 ± $441</td>
</tr>
<tr>
<td>Capital Cost:</td>
<td>$19,000 ± $5,000</td>
</tr>
<tr>
<td>Operating Cost:</td>
<td>$21,961 ± $5,000</td>
</tr>
<tr>
<td>% Satisfied Demand:</td>
<td>85.4% ± 1.2%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>32 ± 1</td>
</tr>
<tr>
<td>Treated:</td>
<td>412 ± 22</td>
</tr>
<tr>
<td>Partials:</td>
<td>313 ± 23</td>
</tr>
<tr>
<td>Untreated:</td>
<td>185 ± 54</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>4,040 ± 294</td>
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</table>

### Optimized (ES 3: 90% demand satisfied for hospitals and health centers)

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</thead>
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<td><strong>Mean ± SD</strong></td>
<td><strong>Mean ± SD</strong></td>
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<tr>
<td>Total Cost:</td>
<td>$11,161 ± $1,111</td>
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<tr>
<td>Capital Cost:</td>
<td>$5,000 ± $0</td>
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<td>Operating Cost:</td>
<td>$17,961 ± $5,000</td>
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<tr>
<td>% Satisfied Demand:</td>
<td>91.1% ± 1.4%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>32 ± 1</td>
</tr>
<tr>
<td>Treated:</td>
<td>412 ± 22</td>
</tr>
<tr>
<td>Partials:</td>
<td>313 ± 23</td>
</tr>
<tr>
<td>Untreated:</td>
<td>185 ± 54</td>
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<tr>
<td>L Delivered (1000s):</td>
<td>4,040 ± 294</td>
</tr>
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</table>

### Optimized (ES 4: Maximum scenario)

<table>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean ± SD</strong></td>
<td><strong>Mean ± SD</strong></td>
</tr>
<tr>
<td>Total Cost:</td>
<td>$49,540 ± $213</td>
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<tr>
<td>Capital Cost:</td>
<td>$23,771 ± $0</td>
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<tr>
<td>Operating Cost:</td>
<td>$11,209 ± $213</td>
</tr>
<tr>
<td>% Satisfied Demand:</td>
<td>91.1% ± 1.4%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>32 ± 1</td>
</tr>
<tr>
<td>Treated:</td>
<td>412 ± 22</td>
</tr>
<tr>
<td>Partials:</td>
<td>313 ± 23</td>
</tr>
<tr>
<td>Untreated:</td>
<td>185 ± 54</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>4,040 ± 294</td>
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**Combined Results for All Health Facilities**

<table>
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<th>Mean ± SD</th>
<th>Mean ± SD</th>
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<tbody>
<tr>
<td>Total Cost:</td>
<td>$104,597 ± $623</td>
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<tr>
<td>Capital Cost:</td>
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<td>Operating Cost:</td>
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<tr>
<td>% Satisfied Demand:</td>
<td>91.1% ± 1.4%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>32 ± 1</td>
</tr>
<tr>
<td>Treated:</td>
<td>412 ± 22</td>
</tr>
<tr>
<td>Partials:</td>
<td>313 ± 23</td>
</tr>
<tr>
<td>Untreated:</td>
<td>185 ± 54</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>4,040 ± 294</td>
</tr>
</tbody>
</table>

**Cost-effectiveness Measures:**

- L / year (1000s): 841
- $ / year: $6,076
- $ / treated: $60,330
- $ / 1000L: $7,136

- $ / life saved: $897
- $ / child treated: $5,051
- $ / DALY averted: 1018

- DALY averted: $23,727
- $ / DALY averted: $23,727

- DALY averted: $23,727
- $ / DALY averted: $23,727

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- L / year (1000s): 841
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- $ / 1000L: $7,136

- $ / life saved: $897
- $ / child treated: $5,051
- $ / DALY averted: 1018

- DALY averted: $23,727
- $ / DALY averted: $23,727

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- $ / child treated: $5,051
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- DALY averted: $23,727
- $ / DALY averted: $23,727

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- DALY averted: $23,727
- $ / DALY averted: $23,727

**Cost-effectiveness Measures:**

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- $ / treated: $60,330
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- $ / life saved: $897
- $ / child treated: $5,051
- $ / DALY averted: 1018

- DALY averted: $23,727
- $ / DALY averted: $23,727
Appendix E. Detailed OxOpt Model Results for The Gambia Case Study

### Figure E.2: Sensitivity analysis: Calculated lives saved for different case fatality rates (CFR) for treated and untreated patients.

(A) Analysis setup: % reduction in case fatality rate for different combinations of $\rho_t$ (treated with oxygen) and $\rho_u$ (untreated). The default used in all scenarios is $\rho_u = 15\%$ and $\rho_t = 10\%$ (i.e., a 33% reduction in mortality risk); (B) - (F) Mean number of lives saved (with standard deviation in parentheses) recalculated for all combinations of $\rho_t$ and $\rho_u$ for the status quo scenario and all equity scenarios (ES 1 to 4) from section 8.5.2. Default condition is outlined.

#### Table A: % REDUCTION IN CFR

<table>
<thead>
<tr>
<th>CFR Treated, $\rho_t$</th>
<th>8%</th>
<th>10%</th>
<th>12%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% CFR Not Treated, $\rho_u$</td>
<td>20%</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>15%</td>
<td>47%</td>
<td>20%</td>
<td></td>
</tr>
<tr>
<td>20%</td>
<td>60%</td>
<td>40%</td>
<td></td>
</tr>
</tbody>
</table>

#### Table B: STATUS QUO SCENARIO

<table>
<thead>
<tr>
<th>CFR Treated</th>
<th>8%</th>
<th>10%</th>
<th>12%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>13.5 (0.6)</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>15%</td>
<td>47.4</td>
<td>33.9</td>
<td>20.3</td>
</tr>
<tr>
<td>20%</td>
<td>81.3</td>
<td>67.7</td>
<td>54.2</td>
</tr>
</tbody>
</table>

#### Table C: EQUITY SCENARIO 1

<table>
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<tr>
<th>CFR Treated</th>
<th>8%</th>
<th>10%</th>
<th>12%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% CFR Not Treated, $\rho_u$</td>
<td>24.5</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>15%</td>
<td>85.7 (4.0)</td>
<td>61.2 (2.8)</td>
<td>36.7 (1.7)</td>
</tr>
<tr>
<td>20%</td>
<td>146.9 (6.8)</td>
<td>122.4 (5.7)</td>
<td>97.9 (4.5)</td>
</tr>
</tbody>
</table>

#### Table D: EQUITY SCENARIO 2

<table>
<thead>
<tr>
<th>CFR Treated</th>
<th>8%</th>
<th>10%</th>
<th>12%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>31.3 (1.4)</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>15%</td>
<td>109.7 (5.0)</td>
<td>78.4 (3.6)</td>
<td>47.0 (2.1)</td>
</tr>
<tr>
<td>20%</td>
<td>188.1 (8.6)</td>
<td>156.7 (7.2)</td>
<td>125.4 (5.7)</td>
</tr>
</tbody>
</table>

#### Table E: EQUITY SCENARIO 3

<table>
<thead>
<tr>
<th>CFR Treated</th>
<th>8%</th>
<th>10%</th>
<th>12%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% CFR Not Treated, $\rho_u$</td>
<td>33.4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>15%</td>
<td>116.8 (4.3)</td>
<td>83.4 (3.1)</td>
<td>50.1 (1.9)</td>
</tr>
<tr>
<td>20%</td>
<td>200.3 (7.4)</td>
<td>166.9 (6.2)</td>
<td>133.5 (4.9)</td>
</tr>
</tbody>
</table>

#### Table F: EQUITY SCENARIO 4

<table>
<thead>
<tr>
<th>CFR Treated</th>
<th>8%</th>
<th>10%</th>
<th>12%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>37.0 (1.0)</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>15%</td>
<td>129.6 (3.4)</td>
<td>92.6 (2.4)</td>
<td>55.5 (1.4)</td>
</tr>
<tr>
<td>20%</td>
<td>222.2 (5.7)</td>
<td>185.1 (4.8)</td>
<td>148.1 (3.8)</td>
</tr>
</tbody>
</table>
## Appendix E. Detailed OxOpt Model Results for The Gambia Case Study

### Table: Combined Results for All Health Facilities

<table>
<thead>
<tr>
<th></th>
<th>Hospitals</th>
<th>Health Centres</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SIMULATED</strong></td>
<td>Mean ± SD</td>
<td>Mean ± SD</td>
</tr>
<tr>
<td><strong>(ES 2 solution for norm scenario)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Cost:</td>
<td>$34,415 ± $279</td>
<td>$42,526 ± $335</td>
</tr>
<tr>
<td>Capital Cost:</td>
<td>$23,771 ± $0</td>
<td>$32,401 ± $0</td>
</tr>
<tr>
<td>Operating Cost:</td>
<td>$10,644 ± $279</td>
<td>$10,125 ± $335</td>
</tr>
<tr>
<td>% Satisfied Demand:</td>
<td>86.1% ± 5.2%</td>
<td>84.0% ± 4.1%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>49 ± 3</td>
<td>30 ± 2</td>
</tr>
<tr>
<td>Treated:</td>
<td>936 ± 59</td>
<td>552 ± 32</td>
</tr>
<tr>
<td>Partial:</td>
<td>81 ± 13</td>
<td>77 ± 7</td>
</tr>
<tr>
<td>Untreated:</td>
<td>132 ± 57</td>
<td>75 ± 30</td>
</tr>
<tr>
<td>Total Patients:</td>
<td>1,149 ± 30</td>
<td>704 ± 24</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>5,041 ± 387</td>
<td>2,992 ± 197</td>
</tr>
</tbody>
</table>

### Table: Combined Results for All Health Facilities

<table>
<thead>
<tr>
<th></th>
<th>Hospitals</th>
<th>Health Centres</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SIMULATED</strong></td>
<td>Mean ± SD</td>
<td>Mean ± SD</td>
</tr>
<tr>
<td><strong>(ES 2 solution for CC1 scenario)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Cost:</td>
<td>$35,661 ± $345</td>
<td>$43,511 ± $308</td>
</tr>
<tr>
<td>Capital Cost:</td>
<td>$23,771 ± $0</td>
<td>$32,401 ± $0</td>
</tr>
<tr>
<td>Operating Cost:</td>
<td>$11,890 ± $345</td>
<td>$11,110 ± $308</td>
</tr>
<tr>
<td>% Satisfied Demand:</td>
<td>83.6% ± 6.3%</td>
<td>82.2% ± 5.1%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>73 ± 5</td>
<td>45 ± 3</td>
</tr>
<tr>
<td>Treated:</td>
<td>1,341 ± 107</td>
<td>827 ± 56</td>
</tr>
<tr>
<td>Partial:</td>
<td>224 ± 29</td>
<td>134 ± 15</td>
</tr>
<tr>
<td>Untreated:</td>
<td>230 ± 111</td>
<td>129 ± 53</td>
</tr>
<tr>
<td>Total Patients:</td>
<td>1,795 ± 34</td>
<td>1,090 ± 34</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>7,586 ± 565</td>
<td>4,514 ± 364</td>
</tr>
</tbody>
</table>

### Table: Combined Results for All Health Facilities

<table>
<thead>
<tr>
<th></th>
<th>Hospitals</th>
<th>Health Centres</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SIMULATED</strong></td>
<td>Mean ± SD</td>
<td>Mean ± SD</td>
</tr>
<tr>
<td><strong>(ES 2 solution for CC2 scenario)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Cost:</td>
<td>$37,351 ± $404</td>
<td>$45,159 ± $310</td>
</tr>
<tr>
<td>Capital Cost:</td>
<td>$23,771 ± $0</td>
<td>$32,401 ± $0</td>
</tr>
<tr>
<td>Operating Cost:</td>
<td>$13,580 ± $404</td>
<td>$12,758 ± $310</td>
</tr>
<tr>
<td>% Satisfied Demand:</td>
<td>80.8% ± 4.9%</td>
<td>81.1% ± 5.3%</td>
</tr>
<tr>
<td>Lives Saved:</td>
<td>108 ± 7</td>
<td>70 ± 5</td>
</tr>
<tr>
<td>Treated:</td>
<td>1,844 ± 124</td>
<td>1,261 ± 97</td>
</tr>
<tr>
<td>Partial:</td>
<td>644 ± 68</td>
<td>273 ± 30</td>
</tr>
<tr>
<td>Untreated:</td>
<td>392 ± 150</td>
<td>220 ± 91</td>
</tr>
<tr>
<td>Total Patients:</td>
<td>2,880 ± 58</td>
<td>1,753 ± 39</td>
</tr>
<tr>
<td>L Delivered (1000s):</td>
<td>11,733 ± 824</td>
<td>7,189 ± 556</td>
</tr>
</tbody>
</table>

### Figure E.3: OxOpt model results for two climate change (CC) scenarios:

Patient admissions increased by 25% (CC1) and 50% (CC2) across all health facilities. Mean ± standard deviation (SD) over 50 simulation iterations. All costs in $USD.