Modelling Forest Fire Initial Attack Airtanker Operations

by

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A thesis submitted in conformity with the requirements for the degree of Masters of Applied Science Graduate Department of Mechanical and Industrial Engineering University of Toronto

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Abstract

The Ontario Ministry of Natural Resources uses airtankers for forest fire suppression that now have onboard GPS units that track their real-time location, velocity and altitude. However, the GPS data does not indicate which fire is being fought, the time each airtanker spends travelling to and from each fire or the time each airtanker spends flying between each fire and the lake from which it scoops water to drop on the fire.

A pattern recognition algorithm was developed and used to determine what was happening at each point along the airtanker’s track, including the time and location of every water pickup. This pre-processed data was used to develop detailed models of the airtanker service process. A discrete-event simulation model of the initial attack airtanker system was also developed and used to show how service process models can be incorporated in other models to help solve complex airtanker management decision-making problems.
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# Table of Contents

Acknowledgements .................................................................................................................................................. iii
List of Tables .......................................................................................................................................................... vi
List of Figures ...................................................................................................................................................... vii

Chapter 1: Introduction ......................................................................................................................................... 1
  1.1 Forest Fire Management in Ontario ........................................................................................................... 1
  1.2 Initial Attack Airtanker System .................................................................................................................. 3
  1.3 Literature Review ........................................................................................................................................ 4
  1.4 Overview of the Thesis ............................................................................................................................... 10

Chapter 2: A Methodology for Extracting Forest Fire Airtanker Service Process Data from Aircraft Tracking System Datasets ......................................................................................................................... 12
  2.1 Introduction ................................................................................................................................................ 12
  2.2 A Brief Technical Description of the CL-415 ............................................................................................. 13
  2.3 The Aircraft Tracking System Database .................................................................................................. 13
  2.4 Airtanker Trips .......................................................................................................................................... 15
  2.5 Matching Airtanker Trips to Fires and Airports ......................................................................................... 17
  2.6 Water Pickup Algorithm .............................................................................................................................. 20
    2.6.1 Validation of the Water Pickup Algorithm ............................................................................................ 23
  2.7 The Airtanker Service Process Database ................................................................................................ 27
    2.7.1 Quality of the Airtanker Service Process Data .................................................................................... 29
  2.8 Summary .................................................................................................................................................... 30

Chapter 3: An Empirical Analysis of Airtanker Service Process Data .................................................................... 31
  3.1 Introduction ................................................................................................................................................. 31
  3.2 Service Time of a Fire ................................................................................................................................. 32
    3.2.1 The Number of Airtankers Dispatched to a Fire .................................................................................. 33
    3.2.2 Fire, Lake and Airport Locations ....................................................................................................... 35
    3.2.3 Current and Forecast Weather Conditions ......................................................................................... 42
    3.2.4 Deployment, Redeployment and Dispatch Strategies ........................................................................ 44
    3.2.5 Summary .............................................................................................................................................. 50
  3.3 Service Process Models ............................................................................................................................... 50
List of Tables

Table 1: List of all airports used for airtanker operations during the 2006 through 2011 fire seasons. Also shown is the number of times each airport was used as a takeoff and landing base. .......................................................... 19
Table 2: An example of ATS data. .......................................................... 22
Table 3: Lognormal parameter estimates....................................................... 38
Table 4: A summary of the base-to-fire distance data by fire region of Ontario .................. 41
Table 5: A summary of the lake-to-fire distance data (partitioned by region of Ontario)........ 41
Table 6: Results of the logistic regression model to predict the probability of dispatching 1 or more airtankers to a fire (n=4846). .......................................................... 48
Table 7: Zero-truncated negative-binomial regression diagnostics ...................... 54
Table 8: Diagnostics of linear regression fit for each airtanker service process. ............... 54
Table 9: Lognormal parameter estimates.......................................................... 65
Table 10: Service process models that were developed and described in Chapter 3 .......... 69
Table 11: Fire arrival rate table........................................................................ 74
Table 12: Mann-Whitney U test to determine if the response time data was significantly different between redeployment strategies for two different fire load scenarios. .......................... 80
List of Figures

Figure 1: Fire regions of Ontario. ........................................................................................................... 2
Figure 2: Simple timeline of airtanker events. .......................................................................................... 9
Figure 3: Process flow diagram of an airtanker trip. ................................................................................. 16
Figure 4: Map of all airports used for airtanker operations during the 2006 through 2011 fire seasons. ........................................................................................................................................... 20
Figure 5: Altitude and speed readings from airtanker MNR4821 during a twenty minute period of the 2011 fire season. .................................................................................................................. 22
Figure 6: Airtanker MNR4867 completing one cycle of the drop process on fire KEN 104 between 10:30 pm GMT and 10:34 pm GMT on August 23, 2011. Pickup points are labelled "pick up" in the figure. ........................................................................................................................................... 25
Figure 7: Airtanker MNR 4867 dropping 16 loads of water on fire KEN 104 between 10:00 pm GMT and 11:00 pm GMT on August 23, 2011. Pickup points are labelled "pick up" in the figure. ........................................................................................................................................... 26
Figure 8: Box and whisker plot of the service time for fires with different number of airtankers. ........................................................................................................................................... 34
Figure 9: Proportion of airtanker fires that were assigned 1, 2, 3 or more than 3 airtankers for initial attack. ........................................................................................................................................... 35
Figure 10: Histogram of the base-to-fire distance data (n = 701) with a fitted lognormal distribution. ........................................................................................................................................... 38
Figure 11: Q-Q plot comparing the sample base-to-fire distance data with the predicted data from a lognormal distribution. ........................................................................................................................................... 39
Figure 12: Histogram of the lake-to-fire distance data (n = 393) with a fitted lognormal distribution. ........................................................................................................................................... 40
Figure 13: Q-Q plot comparing the sample lake-to-fire distance data with the predicted data from a lognormal distribution. ........................................................................................................................................... 40
Figure 14: Service time as a function of the Fire Weather Index (FWI). .................................................... 43
Figure 15: Service time as a function of the Daily Severity Rating (DSR). .................................................. 44
Figure 16: Airtanker AT2 travels a distance D21 to fire F1, which occurred at time T1. .......................... 45
Figure 17: Airtanker AT1 travels a distance D12 to fire F2 (which occurred at time T1) while airtanker AT2 is still fighting fire F1. ........................................................................................................................................... 45
Figure 18: If the timing, occurrence and location of the fires F1 and F2 were known with certainty, a fire manager would deploy airtanker AT1 to fire F1 and airtanker AT2 to fire F2 to minimize the total distance travelled. ........................................................................................................................................... 46
Figure 19: Different initial deployment for airtankers AT1 and AT2. ....................................................... 47
Figure 20: Empirical and fitted dispatching probabilities as a function of a flame area index (in hundreds of meters squared). The empirical and fitted models are represented by the set of discrete points and the continuous curve, respectively. ........................................................................................................................................... 49
Figure 21: Histogram of the number of drops per fire. .............................................................................. 51
Figure 22: Histogram of the number of drops per fire when the number of drops is less than or equal to 35.......................................................... 52
Figure 23: ZT Poisson and negative binomial distributions fitted to the drop data............. 53
Figure 24: Travel time as a function of base-to-fire distance with residual and Q-Q plots. The Q-
Q plot compares the residual data with the predicted data from a normal distribution. See Table 8
for the fitted equation of the base-to-fire travel time model............................................. 55
Figure 25: Drop time as a function of lake-to-fire distance with residual and Q-Q plots. The Q-
Q plot compares the residual data with the predicted data from a normal distribution. See Table 8
for the fitted equation of the lake-to-fire travel time model.................................................. 56
Figure 26: Travel time as a function of fire-to-base distance with residual and Q-Q plots. The Q-
Q plot compares the residual data with the predicted data from a normal distribution. See Table 8
for the fitted equation of the fire-to-base travel time model............................................... 57
Figure 27: Drop process speed as a function of lake-to-fire distance for straight-line and circular
flight path assumptions. Also included is the assumption from Islam et al. (2009) regarding
average airtanker speed during the entire portion of the trip.................................................. 59
Figure 28: Speed profiles for base-to-fire and fire-to-base portions of the airtanker’s trip. Also
plotted are the average speed assumptions made by Bombardier (Bombardier Website, 2012), the
OMNR (Personal Communication, Joe Eder OMNR), and Islam et al. (2009). ......................... 60
Figure 29: Circular flight path assumption overestimates the distance travelled. This figure
shows airtanker making drops on KEN 104 between 10:00 pm GMT and 11:00 pm GMT on
August 23, 2011.......................................................................................................................... 61
Figure 30: Circular flight path assumption underestimates the distance travelled. This figure
shows airtanker MNR4867 making drops on RED 26 between 7:40 pm GMT and 9:00 pm GMT
on July 5, 2011............................................................................................................................ 62
Figure 31: Histogram of the on-scene time with a fitted lognormal distribution. .................. 64
Figure 32: Q-Q plot comparing the sample on-scene time data with the predicted on-scene time
data............................................................................................................................................. 65
Figure 33: Histogram of service times for initial attack fires with a fitted lognormal distribution
and Erlang distribution.................................................................................................................. 67
Figure 34: Q-Q plot comparing the sample service time data with the predicted service time data
from an Erlang distribution......................................................................................................... 67
Figure 35: Q-Q plot comparing the sample service time data with the predicted service time data
from a lognormal distribution.................................................................................................... 68
Figure 36: Fires arrive uniformly inside the boundaries of the boxed region that is 450 x 300 km
in size............................................................................................................................................ 75
Figure 37: Initial deployment of airtankers at airports in the West Fire Region...................... 79
Figure 38: Average response time (hr.) to fires that arrive at various times of the day, for two fire
load scenarios (20, 30 fires/day) and two redeployment strategies (home base, closest base).... 80
Chapter 1: Introduction

1.1 Forest Fire Management in Ontario

In 2011, 1,334 forest fires burned approximately 635,374 hectares in the province of Ontario. Although the Ontario Ministry of Natural Resources (OMNR) spent approximately $230 million on their forest fire operations program in 2011 ($110 million more than the yearly average) to help curb the damage caused by forest fires, the 2011 fire season had the most area burned in the last 50 years. In addition, health concerns from smoke and direct fire threat forced 4,476 people from their homes across several northern Ontario communities.

The Aviation, Forest Fire and Emergency Services (AFFES) branch of the OMNR is responsible for the management of forest fires across most of the province. In addition to the monitoring of the provincial fire situation and the resource allocation decisions that take place at the Ministry Emergency Operations Centre in Sault Ste. Marie, there are regional forest fire response centres in Sudbury and Dryden that are responsible for daily fire operations in the East and West fire regions of Ontario\(^1\), respectively.

The AFFES engages in many activities that help reduce fire losses, which includes forest fire planning (e.g., where to deploy suppression resources at the beginning of each day), detecting fires with surveillance aircraft before they can grow to large sizes, monitoring small fires and dispatching initial attack crews to contain small fires that may pose a significant threat to nearby values, and the coordination and mobilization of suppression resources to large fires. Although it may appear that the AFFES focuses most of their efforts on minimizing the damage caused by forest fires, there a number of environmental, social, and economic criteria that they consider when developing their strategy for forest fire management (Ministry of Natural Resources Forest Fire Management Strategy for Ontario, 2004).

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\(^1\) See Figure 1 for a map of the forest fire management regions of Ontario.
An important component of the forest fire management system in Ontario is the initial attack subsystem which is designed to quickly dispatch firefighters and/or aircraft so that they can begin suppression action on newly reported fires as soon as possible. The three to five person ground crew is supervised by a crew leader who is usually designated the initial attack fire boss or incident commander (IC). The IC’s primary objective is to contain initial attack fires as quickly as possible. Most fires are detected and reported small enough to be controlled by initial attack forces. However, fires occasionally ‘escape’ initial attack, and are subsequently declared as extended attack fires that may require suppression efforts over an extended period of days or weeks in order to achieve containment. Any dispatched aircraft will be supervised by an air attack officer who is monitoring the fire in a “Bird Dog” aircraft and establishes contact with the fire boss in order to coordinate ground and aerial-based suppression efforts. The majority of aerial firefighting is done by the nine CL-415 airtankers that the OMNR owns and operates specifically for suppressing forest fires.
The CL-415 is an amphibious waterbomber - meaning it can land on an airport runway or bodies of water. It also has the capability to fly just above the surface of a lake or river and scoop up water simultaneously. They are typically used for firefighting in the following way. Upon receiving a report of a fire that has been determined to require aerial suppression, a fire manager will dispatch one or more airtankers to the scene of the fire. An airtanker will usually arrive well within an hour of being dispatched (depending on the distance to be travelled and the cruising speed), after which it can commence suppression actions. Typically the airtanker pilots are directed by the air attack officer to a nearby lake or river from which a load of water can be scooped off the surface. The pilots fly the airtanker back to the fire with a full load of water, and are subsequently directed by the air attack officer to drop the load onto a selected drop zone. After completing several drops, the airtanker either returns to base or is dispatched to another fire where it continues suppression efforts until fuel reserves run low - requiring the airtanker to return to its base.

The goal of the air attack officer (in coordination with the ground-based IC) is to reduce the intensity of the fire by dropping water on the active flame front and/or build a wetted area on and around the fire with successive water drops. This suppression method usually delays the growth of the fire until ground suppression crews to reach the fire and begin direct suppression efforts and in some cases, it virtually extinguishes the fire. Airtankers are extremely effective fire fighting resources for the AFFES because they have the ability to drop thousands of litres of water onto the fire every few minutes (depending on the lake or river’s proximity to the fire). Since airtankers can be more effective than other suppression resources, fire managers devote significant effort determining how best to utilize their fleet of airtankers.

1.2 Initial Attack Airtanker System

Each day forest fire managers must decide how many airtankers to deploy, where to deploy them at the start of the day and how to re-deploy them throughout the day to minimize their response time to fires. Since fires can grow in size and intensity while they wait to receive suppression action, minimizing the response time is critical. Fire managers must consider the risk of having insufficient airtankers available for dispatch to fires during periods of high fire activity.
Not all fires are fought by airtankers. If a fire manager, upon receipt of the report of a fire, determines that the fire poses no significant threat to any communities or values, then a ranger crew of three to five firefighters may be dispatched to the fire by helicopter or truck if airtanker support is not required.

For fires that require airtanker support, a fire manager must decide how many airtankers to dispatch to the fire and where they should be sent from. This is a very complex decision-making problem. The final decision is based on a subjective assessment of the situation that is often based on years of experience. Fire managers will consider the characteristics of the fire, the current and forecast weather conditions, commercial and non-commercial values at risk, the current availability of airtankers, and the expected fire occurrence for the remainder of the day when deciding how many airtankers to dispatch to a fire. McAlpine and Hirsch (1999) consulted experienced dispatchers who identified four criteria (rate of spread, fire size, flame length, and fuel type) upon which dispatch decisions were made. If all airtankers are busy, however, the fire is placed in an initial attack queue and served once an airtanker becomes available. The fire may also be removed from the queue if an initial attack crew has contained the fire before the next airtanker becomes available, or if the fire's behaviour has changed due to a sudden change in weather conditions and no longer poses a significant threat to the safety of communities and other values.

1.3 Literature Review

Most of the decision-making problems related to management of the initial attack airtanker system (IAAS) can be classified as one of the following: strategic, tactical, or operational. Strategic decision-making is long term, for example a forest fire management organization is looking to acquire additional airtankers to augment their fleet, or perhaps they are trying to decide where to build an additional base at which airtankers can be deployed. The daily deployment of airtankers is an important tactical decision making-problem that attracts a lot of attention from researchers. An example of operational decision-making is what type and how many resources to dispatch to a particular fire.

To help fire managers make these important decisions, models of the IAAS have been developed using mathematical programming, queueing theory and simulation modelling techniques.
Mathematical programming has been used in a number of studies to model the daily deployment of airtankers. Hodgson and Newstead (1978) investigated the use of location-allocation models for assigning airtankers to potential airports. They present two simple binary mathematical programming models for one-strike initial attack of forest fires by airtankers. Both models try to achieve maximum coverage of values at risk, but the second model emphasizes the importance of minimizing air attack distance. Hodgson and Newstead (1983) extended their own work (discussed above) by considering four airtanker location-allocation models. The models individually focus on 1) minimization of aggregate weighted base-to-fire distances, 2) minimization of the maximum base-to-fire distance, 3) maximizing the number of value-weighted fires while trading off the minimization of base-to-fire distances, and 4) maximizing coverage of fires while minimizing average base-to-fire distance.

MacLellan and Martell (1996) developed an integer linear programming model that specifies how many airtankers to allocate to each airtanker base in Ontario. Their objective was to minimize the cost of satisfying daily airtanker demands, which was assessed subjectively by the OMNR’s Working Group on airtanker allocation.

Haight and Fried (2007) developed a wildland fire suppression resource deployment model. To address the deployment problem, they formulated a scenario-based standard response model with two objective functions: 1) the number of suppression resources deployed, and 2) the expected daily number of fires that do not receive a standard response, which they define as the desired number of resources that can reach the fire within a specified response time.

Hu and Ntaimo (2008) developed a stochastic mixed-integer programming model for firefighting resource optimization. They tested the performance of various resource dispatch plans using fire spread and fire suppression simulation models. Fire managers may use such an integrated framework for supporting resource dispatch plans before resources are sent to the fire.

Another method is to treat the IAAS as a queueing system. The description and classification of queueing systems, including the IAAS, has historically been done using Kendall’s $A/B/C$ notation\(^2\), where $A$ denotes the arrival process, $B$ denotes the service time distribution, and $C$

\(^2\) Kendall's notation for describing and classifying a queueing model that represents a queueing system (Kendall 1953).
represents the number of servers. It is reasonable to assume that the IAAS can be represented as a spatially distributed, time-dependent queueing system with fires as customers that arrive at rates that vary temporally throughout the day and spatially across the landscape, and with airtankers as mobile servers that are based at airports.

In the context of the IAAS, the service time of a fire is defined as the difference between when the first airtanker powers on and when the last assigned airtanker powers down at an airport. It is important to note that there is a delay between the time when a pilot receives notice that he or she is assigned to a fire and when the airtanker is ready for takeoff. The length of this delay depends on the pilot’s alert status, which will vary based on the day’s anticipated fire load. The AFFES alert status system is as follows (Grant Gauthier, OMNR, personal communication, January 19, 2012):

1. Red Alert – Immediate dispatch and departure of resources.
2. Yellow Alert – Maximum of 30 minutes from dispatch to departure.
3. 4 stages of Blue Alert (Blue 1, 2, 3, 4) - Maximum of 1, 2, 3, 4 hours from dispatch to departure.

In reality, a pre-travel delay should be included in IAAS queueing models; however, it is generally assumed that available airtankers are dispatched to fires immediately. This may be due to the lack of available alert status data or perhaps that the pre-travel delay is complex in nature and depends on a number of factors (e.g., expected fire load, quantity and type of available suppression resources). An analysis of the pre-travel delay and its impact on key performance indicators such as the response time would be of great benefit to all stakeholders. Unfortunately, it is beyond the scope of this thesis since our focus is on the service time of fires.

A number of studies have adopted these queueing models of airtanker systems and used an Erlang distribution with $k$ phases, $E_k$, to represent the service time of fires. Bookbinder and Martell (1979) addressed a queueing problem found in helitack operations. The authors modeled the deployment of helicopters that transport initial attack crews to fires as a time-dependent queueing system. In order to minimize the total damage caused by fires in a region, a number of helicopters need to be available to transport fire fighters to the scene of a fire when called upon. The system of differential equations describing this queueing system was solved in order to
compute the expected number of fires awaiting service throughout the day. The results of these calculations were used as inputs into a dynamic programming model, which was then used to determine the optimal allocation of helicopters to bases.

In 1983, Quebec owned and operated 21 CL-215 airtankers (predecessor to the CL-415) that were deployed at a maximum of 13 regional bases across the province. Fortin (1989) treated each region of Quebec’s initial attack airtanker system as an $M(t)/G/\infty$ queueing system. She studied historical records and found that the number of airtanker fires\(^3\) never exceeded 11 on any given day, which was less than the total number of airtankers. She assumed that if the fleet of airtankers were deployed reasonably well across the province under this level of fire activity, that an airtanker would almost always be available for service and the system would rarely be congested. The absence of congestion is a feature of the infinite-server queueing system, which she deemed to be a reasonable representation of Quebec’s initial attack airtanker system at that time. From her analysis of Quebec’s airtanker data, Fortin found that an Erlang distribution could be used to approximate the airtanker service time of a fire. In addition, she observed that the service time was significantly different when multiple airtankers were used to fight a fire during more extreme fire weather conditions. She fitted an Erlang distribution to the service time of each combination of airtankers and fire weather index that she found were significantly different using a simple t-test.

Martell and Tithecott (1991) drew on the results of Fortin (1989) and found from Ontario historical fire report and air attack data that it was reasonable to assume that the service time could be represented by an Erlang distribution with parameters that varied by fire danger and the expected number of fires. They modified the helitack queueing model of Bookbinder and Martell (1979) and applied it to airtanker operations in the Northwest region of Ontario, Canada. They partitioned the region into four independent primary attack zones, each containing a single airtanker base. Each attack zone was treated as a time-dependent $M(t)/G/\infty$ queueing system in order to determine how many airtankers would be busy fighting fires at different times of the day.

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\(^3\) Fires to which one or more airtankers were dispatched.
Islam et al. (2009) also drew on the results of Fortin (1989) to model the service time as an Erlang distribution. They developed a more sophisticated representation of the service time, the mean of which was a function of the travel distance to the fire, the airtanker speed, the number of drops of water required for the fire, and the average lake-to-fire distance. Their work focussed on developing a time-dependent spatial queueing model for the daily deployment of airtankers. They developed a spatial deployment heuristic for the finite-capacity queueing system that can be used to determine a good deployment strategy for each time interval while considering time-varying service and fire arrival rates. The expected virtual response time was selected as the measure of system performance and was calculated during each time interval to determine the best deployment of airtankers.

Researchers and forest fire management professionals have also developed discrete-event simulation models to represent the IAAS. Simard (1979) developed a computer simulation model of forest fire suppression with airtankers. The model, which was coded in FORTRAN IV, evaluates airtanker productivity and effectiveness of suppression. As a result of the model, the computer program AIRPRO was created to test different combinations of airtankers and suppression tactics. The optimal combination was the one that minimized the suppression cost plus damage caused by forest fires.

Martell et al. (1984) developed a deterministic computer simulation model in FORTRAN IV that used the average seasonal cost plus loss to evaluate the performance of the initial attack system in the province of Ontario.

Islam and Martell (1998) developed a model that simulates the arrival of fires that are serviced by the nearest available covering airtanker. If no airtanker is available, the fire is placed in the initial attack queues of the covering airtankers. They modelled the service time as the sum of the mobilization time, the travel time to and from the fire, and the on-scene time. They lacked detailed empirical data on airtanker operations and assumed the following: average airtanker speed is 250 km/hr, average time to drop water on a fire is 3 minutes, average getaway time is 5 minutes, lake-to-fire distance varied uniformly between 1 and 10 km, and the number of water drops varied uniformly between 1 and 20. This hypothetical initial attack airtanker system was
used to investigate the impact of airtanker Initial Attack Range and Daily Fire Load on average response time. The model was coded in the SIMSCRIPT II.5 programming language.

The primary advantage of using discrete-event simulation over queueing theory to model the IAAS is that there is no restriction to using relatively simple service time distributions (e.g., exponential, Erlang). In other words, more complex models of the service processes can be used, which include the travel to the fire, the on-scene firefighting, and the travel from the fire and back to base.

As seen in Figure 2, the travel time to the fire begins when the airtanker is powered on and ends when the first pickup of water is made. The on-scene time\(^4\) begins when the first pickup of water is made by an airtanker and ends when the last load of water is dropped on the fire\(^5\). The travel time from the fire and back to the base begins after the last drop has been delivered and terminates once the airtanker is powered down at an airport.

![Simple timeline of airtanker events.](image)

**Figure 2:** Simple timeline of airtanker events.

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\(^4\) The on-scene time can also be represented by the number of water drops multiplied by the average time between drops from one or more fires. The drop time, also referred to as the cycle time, is the time for an airtanker to complete a drop cycle, which includes picking up a load of water, flying to the fire, dropping the load of water on the fire and returning to the lake for the next pickup.

\(^5\) For much larger fires, many drops of water may be required over a long period of time to help slow and/or contain the growth of the fire. Sometimes an airtanker or group of airtankers working on a fire do/does not have enough fuel on reserve to complete the necessary amount of water drops, so additional airtankers will be dispatched to the fire as they become available.
1.4 Overview of the Thesis

A number of studies have focussed on developing decision-support tools to help fire managers solve complex decision-making problems associated with initial attack airtanker management. Most of these studies have assumed a simple functional form of each of the individual service processes. This has primarily been due to the lack of available operational data to be analyzed. Fortunately, with the recent development of new and affordable Global Positioning System (GPS) technologies, accurate aircraft flight-tracking data is now being collected. The AFFES has been tracking nine of their airtankers in real-time using GPS units that were installed on each of the aircraft prior to the start of the 2006 fire season. This real-time data is collected and stored in the Aircraft Tracking System (ATS) database, which has been acquired from the AFFES.

The objective of this thesis is to build airtanker service process models that are based on detailed GPS data and can be used to improve the reliability of current and future decision support models of airtanker systems. Unfortunately, the ATS datasets do not indicate which fire is being fought by which airtanker(s), the time each airtanker spends travelling to and from each fire or the time each airtanker spends flying between each fire and the lake from which it scoops water to drop on the fire.

Chapter 2 contains a discussion of an algorithm that was developed and used to determine which fires were being fought by which airtanker(s). Also discussed is the development of a pattern recognition algorithm that was used to determine 1) what was happening at each point along the airtanker’s track, and 2) the time and location of every water drop on each fire. The chapter concludes with a validation of the algorithms and a presentation of the detailed Airtanker Service Process (ASP) data that has been extracted from the ATS data.

In Chapter 3 is a discussion of the detailed service process models that were developed, and can be used in IAAS simulation models. The anomalies that were witnessed in the ASP data are also discussed, in addition to a discussion of the appropriateness and limitations of the service process models.
Chapter 4 contains an illustration of how the service process models can be used. A simple discrete-event simulation model of the IAAS was developed and can be used in conjunction with service process models to solve a variety of complex decision-making problems.

The thesis concludes with Chapter 5, which contains a summary of the contributions that this work has made, in addition to a discussion of some areas for future research.
Chapter 2: A Methodology for Extracting Forest Fire Airtanker Service Process Data from Aircraft Tracking System Datasets

2.1 Introduction

Analyzing empirical data to detect system/business inefficiencies has become increasingly popular in the last decade (Kohavi et al. 2002). Private businesses and government agencies are looking to maintain or improve their current level of service often with declining budgets and consequently fewer resources. Analyzing emergency response system data in efforts to reduce response times, improve response vehicle coverage or deployment decision-making has always been of interest to operations researchers, but has become increasingly popular due to the development of new and more affordable Global Positioning System (GPS) technology, which has lead to easier and more frequent data collection methods. For example, Harewood (2002) analyzed data from the Barbados Emergency Ambulance Service to model the arrival of rate of calls, the dispatch delay, the average travelling speed, and the on-scene time. Ingolfsson et al. (2003) used data for about 30,000 calls to Edmonton EMS from the summer of 2000 to test the single start station dispatching protocol using a simulation model of emergency medical services in Edmonton, Alberta. Budge et al. (2010) used administrative data from Calgary Emergency Medical Services for high-priority ambulance calls in Calgary, Alberta to conduct an empirical analysis of ambulance travel times.

Although the literature contains many examples of analyses of urban emergency response system data, there has been little work focussed on analyzing empirical data regarding airtanker-use for forest fire suppression. The Aviation, Forest Fire Management and Emergency Services (AFFES) branch of the Ontario Ministry of Natural Resources (OMNR) has equipped each of its CL-415 airtankers with a GPS device that continuously tracks the real-time location of the aircraft. This data is transmitted back to the regional headquarters over a network where it is stored in the OMNR’s Aircraft Tracking System (ATS) database. The ATS data indicates the airtanker’s track (i.e., its location, speed and altitude over time) but it does not indicate which fire is being fought, whether the airtanker is circling and waiting near the fire, which portions of the track are associated with travel to and from the fire, which portions of it are associated with repeatedly flying between the fire and the lake from which the airtanker scoops water to drop on
the fire or when, where or how many drops are made on each fire. This chapter focuses on developing a procedure to match airtanker missions to fires and developing a pattern recognition algorithm that was subsequently used to infer 1) what was happening at each point along the airtanker’s track, 2) the time and location of every water drop and 3) the number of loads of water the airtanker dropped on each fire.

2.2 A Brief Technical Description of the CL-415

The Bombardier CL-415 is an amphibious aircraft that has been used since 1994 for aerial firefighting around the globe. In Canada, 24 CL-415s are owned and operated by the following provincial fire agencies: Ontario (9), Quebec (8), Newfoundland (4) and Manitoba (3).

According to Bombardier (Bombardier, 2012), these airtankers have a normal cruising speed of 180 kt (333 km/hr) and a stall speed of 68 kt (126 km/hr). The airtanker fuel capacity is 10,250 lb and burns fuel at an average rate of 1,660 lb/hr, which implies that a typical trip should not last much longer than 6 hours. At the normal cruising speed, the airtanker can cover approximately 2000 km in 6 hours. However, airtankers do not often travel far from their home base, since they must have enough fuel on reserve to fulfill their firefighting duties and return back to base.

Water scooping is an effective firefighting technique. According to Bombardier (Bombardier, 2012), if a body of water is 1,340 metres long, 90 metres wide and 2 metres deep, then it is safe for a CL-415 to scoop from it. The aircraft only needs about 410 metres on the water to make a pick up, but the remainder is needed for its approach and climb-out. The CL-415 typically travels at 70 kt (130 km/hr) along the body of water to scoop up a 6,137-litre water load (Bombardier, 2012). Therefore, the scooping time is approximately 11-12 seconds. Once the airtanker arrives at the fire with a full load, it is typically travelling at 110 kt (204 km/hr) and will drop its load 30 to 35 metres above the treetop level.

2.3 The Aircraft Tracking System Database

The global positioning system (GPS) devices installed on board each aircraft read information from at least 3 satellites, which transmit location and temporal data back to the device.
OuterLink Corporation’s Communique 4 (CQ 4) GPS tracking devices were installed on all OMNR airtankers prior to the start of the 2006 fire season. These units are equipped with additional sensor inputs that can interface with various onboard aircraft avionics systems so that additional information can be recorded (e.g., fuel levels, engine power output), however this information was not made available to us. The CQ 4 units are set to record tracking information every 30 seconds\(^6\) while an aircraft is powered on. The GPS device relies on triangulating positions from satellite locations, a technique known as trilateration, therefore delays in subsequent recordings may occur if atmospheric conditions or the local terrain cause the satellite signal to be temporarily unavailable (Bajaj et al. 2002). These devices were used to track the following data:

- **TankerID**: Alphanumeric code unique to each aircraft and has the format MNRXXXX, where the Xs denote placeholders for numbers.

- **Date/Time**: The time the data is recorded is formatted to MM/DD/YYYY hh:mm:ss AM/PM\(^7\). The time is recorded in Greenwich Mean Time (GMT).

- **Latitude**: Degrees, minutes, seconds format (e.g., 48:11:56N).

- **Longitude**: Degrees, minutes, seconds format (e.g., 90:36:55W).

- **Altitude**: Recorded in 8 foot intervals (above sea level).

- **Heading**: 0-360 degrees.

- **Speed**: recorded in knots\(^8\).

During the six year period from 2006 to 2011, the OMNR owned, operated, and tracked nine CL-415 airtankers\(^9\). This tracking data was stored into one central ATS database. I decided, however, to partition the original ATS database into smaller files according to the TankerID and year. Since six years of tracking data was available for nine airtankers, there was 54 subsets of

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\(^6\) Some GPS units are improperly configured by technicians when the aircraft undergo maintenance operations. These units instead record data every one or two minutes.  
\(^7\) Occasionally each GPS unit requires servicing. While being serviced, some units were reconfigured to record the date by DD/MM/YYYY.  
\(^8\) 1 knot (kt) = 1 Nautical mile per hour = 1.852 km/hr  
\(^9\) We did not have ATS data for airtankers borrowed from other agencies.
ATS data to analyze. Each subset, $S_i, i = 1, 2, ..., 54$, is composed of a series of $m$ trips, $S_i = \{T_1, T_2, ..., T_m\}$. The beginning and termination of a trip is marked by the powering up and down of the airtanker, respectively. From the convention used by Mason (2005), a trip, $T_i$, is defined as a sequence of $n$ GPS data points, $T_i = \{g_1, g_2, ..., g_n\}$ where a GPS data point $g_c, c = 1, 2, ..., n$ is represented by a tuple $g_c = \{t_c, lat_c, long_c, a_c, s_c, h_c\}$ giving the airtanker’s position as a latitude ($lat_c$), longitude ($long_c$) and altitude ($a_c$) above sea level at time $t_c > t_{c-1}$, along with its speed and heading ($s_c, h_c$). The time between subsequent trips depends on how much refuelling is required following a trip, the fire load, and how much sunlight is left during that particular day. If there is not enough sunlight, then airtankers will not be dispatched to a fire or assigned additional tasks until the following morning.

2.4 Airtanker Trips

When a forest fire is first reported to a forest fire management agency the dispatcher or duty officer decides whether or not an airtanker or multiple airtankers is/are necessary for initial attack based on one or more of the following factors: the fuel type, the proximity of the fire to values at risk, local weather conditions, the known or predicted fire behaviour (e.g., rate of spread, fire size and flame length), the expected fire load in the region, the availability of ground crews and their anticipated travel time to the fire, and the number of airtankers currently available. If an airtanker is dispatched to a fire, then I say an “airtanker trip” begins, and that trip is composed of a series of distinct events that I refer to as “airtanker trip events”:

1. Pilot completes standard pre-flight check, powers up his or her airtanker and prepares for takeoff.
2. Airtanker taxis to the end of the runway and waits for takeoff clearance from the tower.
3. Airtanker accelerates down the runway and takes off once the required speed is achieved.
4. Airtanker travels to the vicinity of the fire on a relatively straight line flight path. Pilot communicates with air attack officer while en route to the fire.
5. Airtanker arrives in close proximity to the fire. I arbitrarily chose this as a 5 km range.
6. Airtanker pilot scouts the fire and the region for usable lakes or rivers under the direction of the air attack officer.
7. An airtanker scoops up water by skimming the surface of a lake or river.
8. Airtanker flies back to the fire.
9. Load of water is dropped on the fire. Airtanker may have to wait while the drop area is cleared of fire crews, resources/equipment, helicopters and/or other response vehicles.
10. If last drop, then airtanker leaves scene of the fire, and proceeds to event 11. Otherwise airtanker returns to the lake, and repeats events 7 through 9 until the required number of drops have been delivered.
11. Travel to next fire or return to a base. If assigned to another fire, proceed to event 4. Else return to a base.
12. Airtanker lands on the runway and comes to a halt.
13. Taxi to ramp.
14. Pilot powers down the airtanker.

Figure 3 summarizes the flow of airtanker trip events.

![Process flow diagram of an airtanker trip.](image)

Unfortunately, there are no records of airtanker status information that indicate when and where an airtanker began or finished a trip. Therefore, the first step of the data processing was to determine how to partition the sequence of ATS data points into a series of trips. Each trip is defined by a series of data points that represent the airtanker travelling from an airport to perform some task (e.g., fight one or more fires) and returning to an airport. The trip processing algorithm
initiates a new trip whenever it finds a long period of time (e.g., 20 minutes) between subsequent data points. Between trips, airtankers are being refuelled or receiving maintenance at the airport. A 20 minute interval was chosen because during a trip, gaps in the data can occur if the signal is temporarily blocked by atmospheric disturbances.

2.5 Matching Airtanker Trips to Fires and Airports

The ATS data indicates the airtanker’s track (i.e., its location, speed and altitude over time) but it does not indicate which fire(s) is/are being fought during the trip, nor the originating and terminating airports. Before I could determine which fires were being fought by which airtankers on which trips, I had to familiarize myself with the OMNR’s fire reporting system, called the Daily Fire Operations Support System (DFOSS). DFOSS is an information system that is used to record information about fire incidents and weather in the province of Ontario. For each reported fire, the initial attack Fire Ranger Crew Leader\(^\text{10}\) records all the required details about the fire into a fire report, which is eventually recorded into DFOSS. At the end of each season, a subset of the information collected in DFOSS is stored in a database that contains historical fire information for every year since 1960. One of the many pieces of information recorded in the fire report is the number of airtankers used for initial attack. Fires that received initial attack from one or more airtankers are referred to as airtanker fires and they are the ones I am interested in studying. After filtering out all non-airtanker fires, a subset of the DFOSS database was created and contained the following information:

- **First_Report_Date**: This is the date/time (format: MM/DD/YYYY hh:mm:ss AM/PM) the fire was first reported to the AFFES.

- **Out_Date**: This is the date/time (format: MM/DD/YYYY hh:mm:ss AM/PM) the fire was declared out.

- **Latitude**: Decimal degrees format (e.g., 48.56).

- **Longitude**: Decimal degrees format (e.g., -90.36).

\(^\text{10}\) The Fire Ranger Crew Leader, also referred to as the Incident Commander, is responsible for overseeing all forest fire operations, including the management and delivery of all forest fire programs and services.
The fire matching algorithm first identifies a set of possible trips that might be matched to each fire. A fire is assigned to a trip if it falls within a 5 km range of the airtanker for at least one point in time during that trip. All the possible combinations of airtanker and fire locations make this matching step a computationally intensive procedure. For example, suppose there were 400 initial attack airtanker fires one season, and an ATS file tracking one aircraft over the same season contained 40,000 recordings – this aspect of my matching procedure would require 16 million calculations to check each possible combination. Next, the algorithm looks at each individual trip and then eliminates all fires that were not active\textsuperscript{11} during the time of that trip. This procedure requires the airtanker's trip date to fall within the fire's report and out date. When the airtanker falls within a 5 km range of an active fire, I say a "fire event" has occurred. It is possible that an airtanker will fly past (within a 5 km range) another active fire while it is heading to its assigned fire; in this case, when there are fire events from different fires on the same trip, my algorithm matches the airtanker trip to the fire where the most of its fire events occurred. This procedure successfully matched 874 airtanker trips to fires.

Each trip starts and ends with the airtanker at an airport. Previous studies (see Maclellan and Martell 1996) only considered 10 airports as potential airtanker home bases in Ontario. Each trip was assigned a departure and arrival airport if at beginning and end of each trip the airtanker's location fell within a 5 km range of any of the listed airports. A 5 km range around each airport was selected because of the uncertainty in the relative location of the runway to the recorded location of the airport and the possibility of an airtanker’s location not being immediately picked up by the GPS unit while it is first powered on and set in motion down the runway\textsuperscript{12}. The airports identified were recorded as either the departure or arrival airport. The list of identified airports did not include every airport used for airtanker deployment from 2006 through the 2011 fire seasons, therefore the list was expanded in an iterative fashion. For those trips where the departure and/or arrival airport was not identified, the coordinates of the unknown airport at the beginning and/or end of the trip were plotted using Google Maps so the airport's name could be identified. That airport was then added to the list of airports used. Table 1 contains the list of the 24 airports that were identified as having been used - to varying degrees - for airtanker

\textsuperscript{11} Active fires are those fires that have yet to be declared out.

\textsuperscript{12} M. Wotton suggested comparing the current altitude, $a_c$, with the average altitude of points along the airport’s runway. Cross-referencing altitudes would help validate the airport matching procedure.
deployment during the 2006 through 2011 fire seasons and Figure 4 shows where each of these airports are located across the province of Ontario.

<table>
<thead>
<tr>
<th>Airport</th>
<th>Code</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Takeoff</th>
<th>Landing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Armstrong</td>
<td>ARM</td>
<td>50.300</td>
<td>-88.91</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Chapleau</td>
<td>CHA</td>
<td>47.820</td>
<td>-83.350</td>
<td>101</td>
<td>97</td>
</tr>
<tr>
<td>Cochrane</td>
<td>COC</td>
<td>49.104</td>
<td>-81.014</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dryden</td>
<td>DRY</td>
<td>49.831</td>
<td>-92.747</td>
<td>174</td>
<td>164</td>
</tr>
<tr>
<td>Elliot Lake</td>
<td>ELL</td>
<td>46.35</td>
<td>-82.56</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Fort Erie</td>
<td>FER</td>
<td>42.92</td>
<td>-78.96</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Fort Frances</td>
<td>FOR</td>
<td>48.652</td>
<td>-93.432</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Geraldton</td>
<td>GER</td>
<td>49.780</td>
<td>-86.930</td>
<td>152</td>
<td>159</td>
</tr>
<tr>
<td>Hearst</td>
<td>HEA</td>
<td>49.71</td>
<td>-83.69</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Kapuskasing</td>
<td>KAP</td>
<td>49.42</td>
<td>-82.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Kenora</td>
<td>KEN</td>
<td>49.782</td>
<td>-94.35</td>
<td>62</td>
<td>59</td>
</tr>
<tr>
<td>Kirkland Lake</td>
<td>KLL</td>
<td>48.21</td>
<td>-79.99</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Moosonee</td>
<td>MOO</td>
<td>51.29</td>
<td>-80.61</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Muskoka</td>
<td>MSK</td>
<td>44.97</td>
<td>-79.31</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Nipigon</td>
<td>NIP</td>
<td>49.015</td>
<td>-88.283</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>North Bay</td>
<td>NOB</td>
<td>46.36</td>
<td>-79.43</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Pickle Lake</td>
<td>PKL</td>
<td>51.446</td>
<td>-90.203</td>
<td>68</td>
<td>64</td>
</tr>
<tr>
<td>Red Lake</td>
<td>RED</td>
<td>51.068</td>
<td>-93.795</td>
<td>64</td>
<td>74</td>
</tr>
<tr>
<td>Sault Ste. Marie</td>
<td>SAU</td>
<td>46.490</td>
<td>-84.490</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Sioux Lookout</td>
<td>SLK</td>
<td>50.114</td>
<td>-91.904</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sudbury</td>
<td>SUD</td>
<td>46.620</td>
<td>-80.800</td>
<td>96</td>
<td>95</td>
</tr>
<tr>
<td>Thunder Bay</td>
<td>THU</td>
<td>48.397</td>
<td>-89.308</td>
<td>132</td>
<td>135</td>
</tr>
<tr>
<td>Timmins</td>
<td>TIM</td>
<td>48.565</td>
<td>-81.371</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>Vermilion Bay</td>
<td>VRB</td>
<td>49.88</td>
<td>-93.43</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1: List of all airports used for airtanker operations during the 2006 through 2011 fire seasons. Also shown is the number of times each airport was used as a takeoff and landing base.
2.6 Water Pickup Algorithm

This section describes the algorithm I developed for determining airtanker drop times. Airtankers cycle between the fire and the lake from which it picks up water that is dropped on the fire. I define the drop time as the time between consecutive drops of water on the fire.

My objective was to develop a drop time versus lake-to-fire distance model, so the algorithm must extract temporal information and distances to the lake from which water is picked up. Determining when subsequent loads of water are dropped on the fire would allow us to approximate the drop times, but it does not give us any information about the distance to a usable
lake. To account for this, I instead identify when and where an airtanker skims water from the
surface of a lake\textsuperscript{13} and define this as a “water pickup event”.

The water pickup algorithm is based on two characteristics of airtanker behaviour that was
observed during a water pickup event: 1) the aircraft speed decreases sharply to ensure a safe
pickup of water, and 2) the aircraft flies at a lower altitude in order to scoop water from a lake.
This is evident in Figure 5, which shows altitude and speed readings from MNR4821 over a
period of twenty minutes during a drop sequence in 2011. The first thing to notice about the plot
is the cyclical behaviour - the pattern repeats itself every 3-4 minutes. Each cycle can be
partitioned into 4 basic events (Refer to labeled points A through E in Figure 5). I hypothesize
that point A, along with point E and other unlabeled troughs (between 1100 and 1150 feet) in the
plot, indicate when the airtanker was making a water pickup\textsuperscript{14}. From point A to point B, altitude
and speed have increased significantly - I infer that the airtanker was travelling from the lake to
the fire. From point B to C, the airtanker is slowing down and flying at a lower altitude to drop a
load of water on the fire. From C to D, the airtanker is heading back towards the water source.
Finally from D to E, the airtanker dives down for another water pickup. In general, there is a
slight decrease in altitude and speed when an airtanker is approaching a fire, presumably to
ensure an accurate drop. The changes in altitude and speed, however, are not nearly as drastic
and repeatable when compared to those associated with water pickups. It is for that reason that
the algorithm was based on identifying water pickups.

\textsuperscript{13} Pickup times are approximations since data is recorded at discrete 30 second time intervals.
\textsuperscript{14} We see in Figure 5 that the altitude levels for each pickup event are slightly different. This is because events are
recorded in 30 second intervals, so the pickup event reading may actually be from when the airtanker was just about
to touch down on the lake or just as it was taking off. Inaccuracies in the GPS readings may have also played a role.
Figure 5: Altitude and speed readings from airtanker MNR4821 during a twenty minute period of the 2011 fire season.

The following paragraphs describe the algorithm in detail, and refer to the subset of ATS data found in Table 2.

<table>
<thead>
<tr>
<th>TankerID</th>
<th>Date/Time</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Altitude (ft.)</th>
<th>Heading (°)</th>
<th>Speed (knots)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MNR4935</td>
<td>06/20/2008 11:13:03 PM</td>
<td>51.88</td>
<td>-90.21</td>
<td>1360</td>
<td>179</td>
<td>133</td>
</tr>
<tr>
<td>MNR4935</td>
<td>06/20/2008 11:13:39 PM</td>
<td>51.88</td>
<td>-90.17</td>
<td>1552</td>
<td>83</td>
<td>164</td>
</tr>
<tr>
<td>MNR4935</td>
<td>06/20/2008 11:14:08 PM</td>
<td>51.89</td>
<td>-90.15</td>
<td>1952</td>
<td>53</td>
<td>171</td>
</tr>
<tr>
<td>MNR4935</td>
<td>06/20/2008 11:14:45 PM</td>
<td>51.88</td>
<td>-90.10</td>
<td>1856</td>
<td>110</td>
<td>160</td>
</tr>
<tr>
<td>MNR4935</td>
<td>06/20/2008 11:15:14 PM</td>
<td>51.87</td>
<td>-90.11</td>
<td>1536</td>
<td>202</td>
<td>111</td>
</tr>
</tbody>
</table>

Table 2: An example of ATS data.

The algorithm determines if the current altitude, $a_c$, is the minimum of the set $(a_{c-2}, a_{c-1}, a_c, a_{c+1}, a_{c+2})$ corresponding to data points recorded at times $t_{c-2} < t_{c-1} < t_c < t_{c+1} < t_{c+2}$, respectively. By including data from 5 consecutive recordings in a time moving window, the aircraft’s behaviour is being analyzed during a 2 minute period ($t_{c+2} - t_{c-2} \approx 120$

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15 M. Wotton suggested comparing the current altitude, $a_c$, with the average altitude of points on the lake or river’s surface on which the airtanker lands before scooping water. Cross-referencing altitudes would likely improve and help validate the pickup algorithm.
seconds). It was determined that this 2 minute period provided sufficient time to capture the aircraft’s behaviour during the pickup portion of the drop cycle.

Analyzing altitude alone is not sufficient to identify a pickup event. This altitude pattern was witnessed during other phases of the airtanker's journey—e.g. aircraft takeoff, landing, in-transit and from the fire. I observed that pickup event speeds rarely exceeded 110 kt (204 km/hr) and did not fall below 30 kt (56 km/hr). Therefore, the current aircraft speed, \( s_c \), was bounded from above (\( \leq 110 \) kt), which removes any potential pickup event during the transit portion of an airtanker's trip. The lower bound on \( s_c (\geq 30 \) kt) removes potential pickup events during takeoff and landing. While analyzing data during takeoff and landing portions of trips, it was noticed that several clusters of data were satisfying the requirements of the pickup algorithm. For this reason an additional speed restriction was implemented and required \( s_{c-2}, s_{c-1}, s_c, s_{c+1}, s_{c+2} > 30 \) kt. The speed over a 2 minute period must not fall below 30 kt because during takeoff (landing), airtanker speed increases from (decreases to) rest, so preceding (following) speed recordings will violate this restriction and not be identified as pickup events.

This algorithm was written in Visual Basic for Applications in Microsoft Excel and was applied to each data set that was recorded in 30 second intervals and contained altitude information.

2.6.1 Validation of the Water Pickup Algorithm

Unfortunately independent (non GPS) data from the OMNR regarding the number of drops was not available to validate the number of drops that were identified by my algorithm. Instead, the water pickup algorithm was validated by visualizing several examples of the ATS data during the drop process using Geographical Information System (GIS) software, ArcMap 10. For instance, Figure 6 shows airtanker MNR 4867 completing one cycle of the drop process on KEN 104\(^{16}\) \{(lat,lon)=(50.238,-94.866)\} between 10:30 pm GMT\(^{17}\) and 10:34 pm GMT on August 23, 2011. Data points are represented by aircraft symbols that are oriented according to the heading information contained in the ATS datasets. The 2011 fire KEN 104 is represented by an orange circle, lakes are shown in blue, and the rest of the landscape is shown in green. Points are

\(^{16}\) OMNR labels fires with three letters corresponding to the district in which it occurred and a number that corresponds to the number of fires that have occurred within that district at the time the fire was reported.

\(^{17}\) GMT = EDT (Eastern Daylight Time) + 4 hours
labelled “pick up” if the algorithm has identified that point as a pickup event. The date/time of recording is also shown next to each point. Figure 7 shows airtanker MNR4867 picking up all 16 loads of water and dropping all of them onto KEN 104 between 10:00 pm GMT and 11:00 pm GMT on August 23, 2011.

From Figure 6 and Figure 7, the pickup algorithm appears to do a good job of determining when and where pickups of water are occurring.
Figure 6: Airtanker MNR4867 completing one cycle of the drop process on fire KEN 104 between 10:30 pm GMT and 10:34 pm GMT on August 23, 2011. Pickup points are labelled "pick up" in the figure.
Figure 7: Airtanker MNR 4867 dropping 16 loads of water on fire KEN 104 between 10:00 pm GMT and 11:00 pm GMT on August 23, 2011. Pickup points are labelled "pick up" in the figure.
2.7 The Airtanker Service Process Database

Extensive airtanker drop information was extracted from the ATS database using the fire matching procedure and water pickup algorithm. This information is compiled into one database, which I called the Airtanker Service Process (ASP) database, and contains the following information:

• TankerID: unique airtanker ID.

• Fire information: year, district, number, FWI\textsuperscript{18}, size at initial attack, fuel type.

• $S_B$: power up time of the airtanker (i.e., when fire service process begins).

• $OS_A$: when airtanker arrives on-scene at the fire. I assume this is the time of the first water pickup. The airtanker may not always fly directly to a usable water source for scooping - often the tanker will fly near the fire and wait while it receives directions from the air attack officer. This definition will suffice for my purpose.

• $OS_D$: when the airtanker departs from the scene of the fire. I define this as the last fire event time.

• $S_F$: power down time of the airtanker (i.e., when fire service process ends).

• $AIR_D, AIR_A$: departure and arrival airports.

• $D_{F,B}, D_{B,F}$: fire-to-base and base-to-fire distances (kilometers).

• $N_{\text{drop}}$: number of water drops (left blank for those data sets that do not contain altitude information, or are recorded in 1-2 minute intervals).

• $T_{i, i = 1,2, \ldots, N_{\text{drops}}}$: time of water pickup $i$.

• $D_{L,F}$: lake-to-fire distances (kilometers).

\textsuperscript{18} See section 3.2.3 for a discussion of the Fire Weather Index (FWI).
In addition to the airtanker service processes, another measure of interest is the lake-to-fire
distance. Fire management organizations in much of Canada, and particularly in Ontario, have
been blessed with an abundance of lakes and rivers. To author’s knowledge, little empirical work
has been done on quantifying the proximity of usable water sources to fires in Ontario. Simard et
al. (1979) determined the average distances between fires and different sizes of usable lakes
during the 1961 through to the 1966 fire seasons. They looked at each fire’s location on a map,
and measured the distance to usable lakes of different sizes near the fire. Knowing the distance to
different sizes of lakes is important because different types and sizes of aircraft require different
sizes of water sources in order to scoop safely. The distance from a fire to a lake suitable for CL-
415 water bombers was determined using the fire’s location (as reported in DFOSS) and the
pickup point in the lake. It was assumed that the fire and lake represent two points that lie on the
surface of a perfect sphere (i.e., assume the Earth is perfectly spherical). In order to calculate the
distance between the two points, the subtended angle was determined using the Haversine
formula, given by:

$$\Delta \hat{\sigma} = 2 \arcsin \left( \sqrt{\sin^2 \left( \frac{\phi_s - \phi_f}{2} \right) + \cos \phi_s \cos \phi_f \sin^2 \left( \frac{\lambda_s - \lambda_f}{2} \right)} \right)$$  

Equation 1: Haversine formula

where $\phi_s, \lambda_s, \phi_f, \lambda_f$ are the geographical latitude and longitude of the two points. This
formulation is numerically more stable for small distance (order of kilometers) calculations than
the usual spherical law of cosines (Sinnott 1984). The usual arc length formula, $d = r \Delta \hat{\sigma}$, where
$r = 6378$ km is the average radius of the Earth, was used to convert the subtended angle to a
distance. This distance calculation was used for determining the base-to-fire and fire-to-base
distances, as well.

The ASP database contains information about specific trips made by airtankers. This database
also contains the following information for specific fires:

• Fire information: year, district, number, FWI, size at initial attack, fuel type.

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19 These fires may or may not have been fought by airtankers.
• $S_B$: power up time of the first airtanker to depart for the fire (i.e., when fire service process begins).

• $OS_A$: when the first airtanker arrives on-scene at the fire.

• $OS_D$: when the last airtanker departs from the scene of the fire.

• $S_E$: power down time of the last airtanker to arrive back to a base (i.e., when fire service process ends).

• $N_{AT}$: the number of airtankers that were found to have worked on the fire. Since the data for airtankers that were borrowed from other agencies was not available, this is a lower bound of the total number of airtankers that actually worked on the fire.

• $N_{drop}$: the number of water drops that I have recorded for the fire. Since the data for airtankers that were borrowed from other agencies was not available, and drop information could not be extracted from all ATS datasets, this is also a lower bound of the total number of water drops on the fire.

2.7.1 Quality of the Airtanker Service Process Data

Since the GPS units onboard two of the airtankers (MNR494B and MNR4865) were not properly interfaced with the aircraft, they did not record altitude during the six year period. As a result, there is no detailed drop information in the ASP database for 206 airtanker trips that were completed by these two airtankers. In addition, the GPS data from a few of the ATS files were recorded in one or two minute intervals. These time intervals do not affect the service times significantly because service times are generally hours long and a one or two minute difference represents a small fraction of the total time. They do, however, have a significant impact on the results of a drop analysis. One and two minute time intervals represent a large fraction of the drop times, which are usually only minutes long. The following test was devised to determine whether or not the data sets recorded in one or two minute intervals were suitable for drop analysis.
The pickup algorithm was applied to two ATS data sets from each of 12 airtanker trips: 1) the original ATS data set recorded in 30 second intervals and 2) the same ATS data set with every second row of data removed for the purpose of mimicking a data set that would be produced with one minute intervals. The results from applying the algorithm to the two data sets for each of the 12 airtanker trips showed that the average difference in the number of drops was 6.6 (average number of drops decreases from 13.6 to 7.00), and the average drop time difference was 2.3 minutes (average drop time increases from 4.6 to 6.9). These differences are far too large to include drop analysis data from the 273 airtanker trips that record GPS data in one or two minute intervals in the ASP database. In total, only 395 of the 874 total airtanker trips contain detailed drop information.

2.8 Summary

For forest fire management agencies like the AFFES branch of the OMNR, tracking their resources, equipment, crews, aircraft, helicopters, and response vehicles in real-time is becoming much easier now that GPS units are more common and relatively inexpensive. I believe that the implementation of GPS tracking devices serves two purposes: 1) it allows fire managers to determine the location of each of their suppression resources in real-time, and 2) archived GPS data can be used to develop detailed models of airtankers, helicopters, and other response vehicle operations that have not previously been studied in detail in the scientific literature due to the lack of available data. To the author’s knowledge, this is the first study that has extracted detailed airtanker trip information from ATS data; since there are no other studies, a novel pattern recognition algorithm was developed, which successfully identified when and where loads of water were being picked up by airtankers. A new method for determining which airtankers were fighting which fires during which trip was also developed.

With the arrival of tracking technology, and the accumulation of GPS data, it is important that we continue to develop methods for extracting useful information from these databases in order to improve resource planning, scheduling, deployment, and dispatch decision-making for the future.
Chapter 3: An Empirical Analysis of Airtanker Service Process Data

3.1 Introduction

Every day forest fire managers are faced with several complex decision-making problems regarding the use of their airtanker fleet. For instance, they must decide where and how many airtankers to deploy at each airport at the beginning of each day; which and how many airtankers to dispatch to a fire; and how to redeploy airtankers throughout the day as the actual weather, and the future fire load changes. To help fire managers with their decision-making problems, a number of models have been developed (see the recent work of Hu and Ntaimo (2008) and Islam et al. (2009)). These models simulate the initial attack airtanker system (IAAS) and how the desired performance metrics (e.g., response time) vary based on the decisions made by forest fire managers. Unfortunately, these models have typically been based on service process models that were assumed to have simple functional forms since very little detailed operational data was available for analysis. For example, Islam et al. (2009) - in their development of a time-dependent spatial queueing model for the daily deployment of airtankers - assumed the following characteristics for airtankers during initial attack: the fixed time to pickup and drop water on a fire is 3 minutes, the lake-to-fire distance varies uniformly between 1 and 10 km, the average airtanker speed is 250 km/hr and the number of water drops varies uniformly between 1 and 20.

To the author’s knowledge, there has not been any other work devoted to modelling airtanker service processes in more detail. However, there have been a few instances of modelling travel times for different types of response vehicles in both the forest fire initial attack and urban emergency response system literature. Hatfield et al. (2004) designed an algorithm that quickly calculates minimum travel times between locations on a network of roads for initial response forest fire suppression units, however they do not consider the use of airtankers. Kolesar et al. (1975) developed a travel time model for fire engines in New York City, as part of the RAND Fire Project (Walker et al. 1979). They found that the average travel time to incidents increases with the square root of travel distance for short runs less than or equal to 1.42 kilometers, and linearly for longer runs. Aladdini (2010) developed a travel time model for ambulances responding to incidents in Waterloo, Ontario. He categorized the trip lengths into twelve 1 km distance categories (from 0 – 12 km) and estimated the mean travel time for each category using
a multiple linear regression model that considers the distance travelled on three separate road types, including highway, regional and municipal roads. He also found that for repeated trips (i.e., the same origin and destination), the travel time could be estimated by a lognormal distribution. Budge et al. (2010) used data for high-priority calls in Calgary, Alberta to estimate how ambulance travel times varies with distance, which typically ranged from 0 – 10 km. They found that Kolesar et al. (1975) travel time model provided a good estimate of median travel times of ambulances in Calgary.

Fortunately, the advancement and improved affordability of global positioning system (GPS) technology has lead to an increase in data collection amongst forest fire management agencies, including the Aviation, Forest Fire and Emergency Services (AFFES) branch of the Ontario Ministry of Natural Resources (OMNR). Since 2006, GPS units have been tracking the location of nine OMNR airtankers in real-time. This Aircraft Tracking System (ATS) database has been acquired and contains airtanker tracking information from the 2006 through 2011 fire seasons—the most precise and detailed data available to date. This GPS data was pre-processed and relevant airtanker trip information was extracted using various algorithms that are discussed in Chapter 2. This trip information (e.g., the travel time of an airtanker to a fire, the number of loads of water dropped on the fire, the average time between drops, and the service time) is stored in what I call the Airtanker Service Process (ASP) database.

This chapter contains a discussion of the ASP data and the service process models that were subsequently developed. With these service process models, one can estimate: 1) the service time of a fire, 2) the number of water drops on a fire, 3) the travel time of flights between the airport and the fire, flights between the fire and the lake from which the airtanker picked up water to drop on the fire, and flights between the fire and the airport, and 4) the on-scene time. The factors that affect the service time of fires in the IAAS are also discussed.

3.2 Service Time of a Fire

For the simple case, when only one airtanker is dispatched to a fire, the service time, $S$, is easily calculated as $S = A - D$, where $A$ is the arrival time of an airtanker back at its base, and $D$ is the departure time (i.e., when it originally left its base). Further calculations are required when multiple airtankers are dispatched as a part of the initial attack team; for $M$ airtankers dispatched
to a fire, there are $M$ entries of departure time and $M$ entries for time of arrival back to base\textsuperscript{20}. Let $D_i, i = 1,2,\ldots, M$ be the departure time of the $i$th airtanker to depart and $A_j, j = 1,2,\ldots, M$ be the arrival time of the $j$th airtanker back at an airport\textsuperscript{21}. Then the service time is calculated as $S = A_M - D_1$. For $M = 1$, this reduces to $S = A_1 - D_1$, as expected.

$$S = \begin{cases} S_{E.M} - S_{B.1} \\ T_{BF.1} + T_{OS} + T_{FB,M} \\ T_{BF.1} + (N_{drops} \times T_{drop}) + T_{FB,M} \end{cases}$$

where $T_{OS} = OS_{D,M} - OS_{A,1}$ is the on-scene time (the time between when the first airtanker arrives on scene ($OS_{A,1}$) and the last airtanker departs the scene of the fire ($OS_{D,M}$)), which can also be expressed as the number of drops on a fire, $N_{drops}$, multiplied by the average drop time, $T_{drop}$. $S_{E,M}$ is the time when the last airtanker is powered down, $S_{B,1}$ is the time when the first airtanker is powered up, $T_{BF.1}$ is the base-to-fire travel time of the first airtanker to power up and $T_{FB,M}$ is the fire-to-base travel time of the last airtanker to power down.

Many studies have discussed the relationship between the service time of forest fires and other factors such as: the number of airtankers used for suppressing a fire; fire, lake and airport locations; current and forecasted weather conditions; characteristics of the fire; and the deployment, redeployment, and dispatching strategies (see Islam and Martell 1988, Islam et al. 2009). However, to the author’s knowledge no one has used empirical airtanker data to develop detailed models of these relationships. In the following sections I will discuss some of these relationships.

3.2.1 The Number of Airtankers Dispatched to a Fire

The number of airtankers dispatched to a fire is subjectively determined by experienced fire managers who consider the characteristics of the fire, current and forecasted weather conditions, the proximity of the fire to nearby communities or other values at risk, and the number and location of available airtankers and other suppression resources at the time a fire is reported.

\textsuperscript{20} The time each airtanker is dispatched to a particular fire, arrives on-scene of the fire and returns to base is often not the same. This must be accounted for when calculating the service time.

\textsuperscript{21} The last airtanker to return to its base may not be the last airtanker to leave the airport.
In general, when more airtankers are dispatched to a fire, the service time tends to be longer (see Figure 8). This is largely because more airtankers are dispatched to: 1) larger fires, 2) more intense fires, 3) faster spreading fires, or 4) fires that are close to communities or other values at risk. In each of these cases the fire will receive more suppression action in hopes of achieving successful containment at a small size.

![Box and whisker plot of the service time for fires with different number of airtankers.](image)

Figure 8: Box and whisker plot of the service time for fires with different number of airtankers.

Although the service time tends to be longer when more airtankers are dispatched, it is quite rare for more than two airtankers to be dispatched to a fire in Ontario. From Figure 9, only about 6% of fires (from 2006-2011) that required airtanker suppression were allocated more than two airtankers for initial attack. In addition, nearly two-thirds of airtanker fires received only one airtanker.

Unfortunately, there are far too many factors that affect the service time of fires for us to determine the sole effect of dispatching additional airtankers. Identical fires should have shorter service times when they are fought with more airtankers because the required number of drops can be delivered in less time. In reality however, additional airtankers are rarely dispatched to
fires for the sole purpose of reducing the service time. Airtankers are extremely expensive to operate and are important to have on reserve in case new fires are reported.

![Bar chart showing proportion of airtanker fires assigned 1, 2, 3, or more than 3 airtankers for initial attack.]

Figure 9: Proportion of airtanker fires that were assigned 1, 2, 3, or more than 3 airtankers for initial attack.

3.2.2 Fire, Lake and Airport Locations

The location of the fire, the lake from which water is being picked up, and the airport from which an airtanker is dispatched are important pieces of information that, when known with certainty, allow upper and lower bounds to be put on the service time. Suppose base $B$, fire $F$, and nearest landable lake $L$ are randomly located on a landscape and have known coordinates $(x_B, y_B)$, $(x_F, y_F)$, and $(x_L, y_L)$, respectively. The base-to-fire distance is defined as $D_{BF} = r \Delta \sigma_{BF}$; the lake-to-fire distance as $D_{LF} = r \Delta \sigma_{LF}$; and the fire-to-base distance as $D_{FB} = D_{BF}$ (in the simple case where it is assume that the airtanker returns to the base from which it was dispatched), where $\Delta \sigma_{BF}$ and $\Delta \sigma_{LF}$ are given by the Haversine formula in Equation 1, and $r = 6378$ km is the
radius of the Earth. Recall that if I assume only one airtanker is dispatched to fire $F$, then the service time can be written as follows\textsuperscript{22}:

$$S = T_{BF} + (N_{drops} \times T_{drop}) + T_{FB}$$

Suppose that there exist\textsuperscript{23} three linear functions $h_1, h_2, h_3$ such that:

$$h_1(D_{BF}) = b_1 + m_1 D_{BF} = T_{BF}$$
$$h_2(D_{LF}) = b_2 + m_2 D_{LF} = T_{drop}$$
$$h_3(D_{FB}) = b_3 + m_3 D_{FB} = T_{FB}$$

where $b_i, m_i \in \mathbb{R}, i = 1,2,3$. If all delays are ignored (e.g., the airtanker has to wait until the bird dog officer has completed his/her assessment of the fire and decided where he/she want the airtanker to drop) the service time can be written as:

$$S = (b_1 + m_1 D_{BF}) + N_{drops} (b_2 + m_2 D_{LF}) + (b_3 + m_3 D_{FB})$$

Assuming $D_{BF} = D_{FB}$ (unless the airtanker returns to a base other than the one from which it was dispatched) and ignoring the effects of wind, the service time can be written as:

$$S = (b_1 + b_3) + (m_1 + m_3) D_{BF} + N_{drops} (b_2 + m_2 D_{LF})$$

$$\Rightarrow S = p + N_{drops}q$$

where $p = (b_1 + b_3) + (m_1 + m_3) r \Delta \sigma_{BF}$, and $q = b_2 + m_2 r \Delta \sigma_{LF}$ are both constants. The service time can therefore be bounded above and below by the following:

$$p + \min(N_{drops})q \leq S \leq p + \max(N_{drops})q$$

If the minimum number of drops, $\min(N_{drops})$, an airtanker makes is 1, then maximum number of drops, $\max(N_{drops})$, can be calculated by the following: suppose an airtanker has $L$ liters of

---

\textsuperscript{22} Note: we have omitted the subscripts for simplicity.

\textsuperscript{23} In Section 3.3.2, linear regression techniques are applied to our ASP travel time data to estimate the coefficients of $h_1, h_2, \text{and } h_3$. 

36
fuel on reserve when it was dispatched to a fire, and it burns its fuel at rate \( R \) (litres/unit distance travelled). Since \( D_{BF} \) and \( D_{FB} \) are known, then the amount of fuel burned while travelling to and from the fire is \( L_{travel} = R(D_{BF} + D_{FB}) = 2RD_{BF} \) (since I assumed \( D_{BF} = D_{FB} \)). The remaining fuel that can be used during the drop process is given by \( L_{drop} = L - L_{travel} \). Assuming that the airtanker begins and ends the drop process at or in close proximity to the fire, the amount of fuel burned during the drop process is given by \( L_{drop} = R(N_{drops} \times \pi D_{LF}) = \pi RD_{LF}N_{drops} \). It follows that the maximum number of drops can be approximated by:

\[
\text{max}(N_{drops}) = \frac{L - 2RD_{BF}}{\pi RD_{LF}}
\]

Where \( \text{max}(N_{drops}) \) is rounded down to the nearest whole number. Therefore, given that the locations of the fire and the nearest landable lake are known, the service time can be restricted by the following:

\[
p + q \leq S \leq p + q \left( \frac{L - 2RD_{BF}}{\pi RD_{LF}} \right)
\]

Although the service time is difficult to predict, if the location of the fire, the lake, and the airport from which the airtanker is dispatched is known, then the estimated service time can at least be bounded.

When fire managers develop their deployment strategies for the next day, the location of tomorrow’s fires and their respective pickup lake are not known. To plan effectively, decision support tools could be used by fire managers to simulate how the initial attack airtanker system will perform under many possible fire occurrence scenarios (e.g., where, how many, and how often fires could occur). Although the focus of this thesis is not to develop a fire occurrence model, some basic statistics were applied to the ASP distance data to summarize the distances travelled during the course of an airtanker mission. Figure 10 shows a histogram of the base-to-fire distance data for all fires \( (n = 701) \) during the study period. The maximum-likelihood parameter estimation method was used to fit a lognormal distribution to the base-to-fire distance data (see Table 3 for parameter estimates). To determine the goodness of fit, a Kolmogorov-Smirnov (KS) test was performed. The test results (see Table 3 for KS test results) suggest that
the lognormal distribution provides a good fit to the base-to-fire distance data. An Anderson-Darling (AD) goodness-of-fit test was also performed and the results indicated the null hypothesis that the data follows a lognormal distribution should be rejected ($p < 0.01$), which suggests that the data does not fit the tails of the lognormal distribution very well. The Q-Q plot in Figure 11 suggests that a lognormal distribution provides a reasonable fit for base-to-fire distance data less than about 200 km.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Sample Size</th>
<th>$\mu$ (Standard Error)</th>
<th>$\sigma^2$ (Standard Error)</th>
<th>KS test</th>
<th>AD test</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_{BF}$</td>
<td>701</td>
<td>4.638 (0.029)</td>
<td>0.751 (0.020)</td>
<td>0.045</td>
<td>0.132</td>
</tr>
<tr>
<td>$D_{LF}$</td>
<td>395</td>
<td>1.466 (0.038)</td>
<td>0.703 (0.027)</td>
<td>0.037</td>
<td>0.756</td>
</tr>
</tbody>
</table>

Table 3: Lognormal parameter estimates.

Figure 10: Histogram of the base-to-fire distance data ($n = 701$) with a fitted lognormal distribution.
Figure 11: Q-Q plot comparing the sample base-to-fire distance data with the predicted data from a lognormal distribution.

An analysis of the lake-to-fire distance data was also performed. Figure 12 shows a histogram of the lake-to-fire distance data \( n = 395 \). The maximum-likelihood approach was used to fit a lognormal distribution to the lake-to-fire distance data (see Table 3 for parameter estimates), and a KS test confirmed the goodness of fit (see Table 3 for KS test results). An Anderson-Darling test was also performed and the results indicated that the null hypothesis that the data follows a lognormal distribution should not be rejected \( (p = 0.585) \). The Q-Q plot in Figure 13 suggests that a lognormal distribution provides a reasonable fit to the lake-to-fire distance data.
Figure 12: Histogram of the lake-to-fire distance data ($n = 393$) with a fitted lognormal distribution.

Figure 13: Q-Q plot comparing the sample lake-to-fire distance data with the predicted data from a lognormal distribution.
Kolesar and Blum (1973) found that the expected distance to an incident that a response vehicle will have to travel is a function of the number of stations with available response vehicles and the size of the response area. With the ASP base-to-fire distance data, I could explore whether Kolesar and Blum’s expected distance model applies to the initial attack airtanker system; unfortunately, the data does not record the location and number of available airtankers at the time of dispatching\textsuperscript{24}. So instead a possible regional effect on the magnitude of the base-to-fire distance was investigated. If the average base-to-fire distance is significantly longer in one fire region, then this suggests that airtankers should be distributed more evenly between regions.

The base-to-fire distance data was categorized by the region of Ontario (EFR, WFR) in which the fire was reported (see Table 4 for a summary of statistics). A Mann-Whitney U non-parametric test (Mann and Whitney, 1947) was used to determine if the base-to-fire distance data differs significantly between the East and West fire regions. The results indicated that the regional effect was not significant (U=50724, $p = 0.27$). Therefore, the base-to-fire distance model could be used reliably in a decision support system that simulated initial attack airtanker operations across the East and West fire regions of Ontario.

<table>
<thead>
<tr>
<th>Fire Region</th>
<th>Average $D_{BF}$ (km)</th>
<th>Standard Error</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>East</td>
<td>138.10</td>
<td>6.68</td>
<td>198</td>
</tr>
<tr>
<td>West</td>
<td>129.26</td>
<td>3.99</td>
<td>486</td>
</tr>
</tbody>
</table>

Table 4: A summary of the base-to-fire distance data by fire region of Ontario.

A Mann-Whitney U test was also used to determine if the lake-to-fire distance data (summarized in Table 5) differs significantly between regions. In this case, the results indicated that the effect was significant (U=19347, $p < 0.05$).

<table>
<thead>
<tr>
<th>Fire Region</th>
<th>Average $D_{LF}$ (km)</th>
<th>Standard Error</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>East</td>
<td>6.34</td>
<td>0.39</td>
<td>131</td>
</tr>
<tr>
<td>West</td>
<td>5.32</td>
<td>0.24</td>
<td>262</td>
</tr>
</tbody>
</table>

Table 5: A summary of the lake-to-fire distance data (partitioned by region of Ontario).

\textsuperscript{24} This information could be extracted from the ATS data, but to develop an appropriate procedure was beyond the scope of this thesis.
3.2.3 Current and Forecast Weather Conditions

Forest fire management agencies across Canada use the Canadian Forest Fire Weather Index System (Van Wagner 1987), a subsystem of the Canadian Forest Fire Danger Rating System (Stocks et al. 1989), which is based upon wind speed, temperature, relative humidity, and 24-hour rainfall readings from local weather stations and is used to generate numeric ratings of fuel moisture and potential fire behaviour in an area surrounding the weather station where the measurements were collected. There are six components of the FWI – three fuel moisture codes, which are numeric ratings of the fuel moisture in distinct layers of the fuel bed, and three fire behaviour indices, which are numeric ratings that represent distinct fire behaviour characteristics.

The three fuel moisture codes are: the Fine Fuel Moisture Code (FFMC), which represents the moisture content in the fine surface fuels (e.g., twigs and small branches); the Duff Moisture Code (DMC), which represents the moisture content in the loosely compacted organic layers; and the Drought Code (DC), which represents the moisture content in the deep compact organic layers.

The three fire behaviour indices are the Initial Spread Index (ISI), the Buildup Index (BUI), and the Fire Weather Index (FWI) and represent the rate of fire spread, the amount of fuel available for combustion, and the potential fire intensity, respectively. These three indices can be used to estimate the potential fire behaviour for a particular fire, but they do not account for the effects of fuel type.

The FWI was expected to be a good predictor of service time since large FWI values indicate hot and dry weather conditions, which can lead to the ignition of more fires and more intense fire behaviour. Unfortunately, Figure 14 indicates that the FWI is not a good predictor of the service time.

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25 The Ontario Ministry of Natural Resources owns and operates 177 weather stations that are strategically located across the province and are each used for calculating the Fire Weather Index in their respective region.
The reason for these poor relationships is no doubt due to the fact that many factors influence these service processes. For example, more airtankers will be dispatched to fires close to values at risk, and an airtanker will spend less time on each fire on days when many fires are reported.

Another relationship I was interested in investigating was how the service time varied with the Daily Severity Rating, which is a numeric rating based on the FWI that has been used as an indicator for the difficulty of fire suppression.

\[ DSR = 0.0272FWI^{1.77} \]

The power law relationship between the DSR and FWI emphasizes the severity of potential fires for large FWI values. From Figure 15, the DSR is not a good predictor of the service time of a fire.

Figure 14: Service time as a function of the Fire Weather Index (FWI).
3.2.4 Deployment, Redeployment and Dispatch Strategies

Every day fire managers must decide where and how many airtankers to deploy at the beginning of each day and how to redeploy them over the course of the day in order to minimize airtanker response time to fires. Fire managers attempt to minimize travel times to fires by deploying airtankers close to areas where fires are expected to occur.

Minimizing the travel time has the potential to significantly reduce the service time. Islam et al. (2009) noted that the total airtanker travel time between the airport and the fire constitutes a very significant portion of the service time - contrary to urban emergency response systems where the vehicle travel times account for a much smaller portion of the service time. For example, during my study period the average airtanker travel time accounted for 54% of the average service time of airtanker fires in Ontario. Takeda et al. (2007), on the other hand, have found that average ambulance travel times in Campinas, Brazil account for only 18% of the average service time.

A fire manager may decide that in order to minimize the travel time and service time, each fire should be assigned the closest-available airtanker. The closest-available dispatch policy may not minimize the travel time in all situations, however. For example, assume there is an initial attack
airtanker system with only two bases and two airtankers, denoted by AT1 and AT2 in Figure 16, which are dispatched to fires using a closest-available policy. At time T1, fire F1 occurs and airtanker AT2 is dispatched since it is the closest-available airtanker. Airtanker AT2 travels a distance D21 to get to fire F1. Now, suppose at time T2, another fire F2 occurs and airtanker AT2 is still suppressing fire F1. Since AT1 is the only available airtanker, it is dispatched to the fire and must travel a distance D12 (see Figure 17). The total distance travelled to both fires is then D21 + D12.

Figure 16: Airtanker AT2 travels a distance D21 to fire F1, which occurred at time T1.

Figure 17: Airtanker AT1 travels a distance D12 to fire F2 (which occurred at time T1) while airtanker AT2 is still fighting fire F1.

If fires F1 and F2 were going to occur at times T1 and T2 and at their respective locations with absolute certainty, then instead of dispatching airtanker AT2 to fire F1 and airtanker AT1 to fire F2, a fire manager would have dispatched airtanker AT1 to fire F1, and then airtanker AT2.
would be sent to fire F2 (see Figure 18) since the total distance travelled would be shorter (D11+D22 < D21 + D12). In this case, a closest-available dispatch policy was not used.

![Diagram](image)

Figure 18: If the timing, occurrence and location of the fires F1 and F2 were known with certainty, a fire manager would deploy airtanker AT1 to fire F1 and airtanker AT2 to fire F2 to minimize the total distance travelled.

From this basic argument, the closest-available strategy should not be used when the timing and location of occurrence for each fire is known with complete certainty. Unfortunately, the exact timing and location of occurrence for each fire will never be able to be predicted. As forest fire occurrence models continue to improve, however, it may be worth investigating alternative dispatch strategies that help minimize the total distance travelled by airtankers.

The total distance travelled will also depend on the deployment of airtankers prior to the ignition of forest fires. If, in the example above, both airtankers (AT1 and AT2) were deployed at the same base (see Figure 19), then the total distance travelled to fires F1 and F2 would be shorter than in the case where the exact timing and location of occurrence for each fire were known (D11* + D22* < D11 + D22). Of course the deployment of airtankers will also depend on the decision maker’s ability to predict when and where fires will occur. Nonetheless, to deploy and dispatch airtankers optimally is a very complex decision-making problem.
Typically in IAAS models, each fire that arrives in the system is assumed to require suppression action from at least one airtanker. In more realistic situations, however, airtankers are not dispatched to every fire as dispatchers often have ground suppression resources available, as well. The contents of the historical fire database for my study period (2006-2011) were analyzed, and the results showed that approximately 34.2% of fires in Ontario (2,112 of 6,180 fires) were allocated at least one airtanker for initial attack. Fire managers assess the situation to determine if and how many airtankers are needed on a fire. McAlpine and Hirsch (1999) consulted experienced dispatchers who identified four criteria (rate of spread, fire size, flame length, and fuel type) upon which dispatch decisions were made. Using historical fire data from the 2006 through 2011 fire seasons, a binomial regression model was developed to predict whether an airtanker will be dispatched to a fire. I defined a binary variable $Y$ such that:

$$
Y = \begin{cases} 
0 & \text{if no airtankers are dispatched} \\
1 & \text{if } \geq 1 \text{ airtankers are dispatched}
\end{cases}
$$

My hypothesis is that $Y$ can be predicted by a surrogate index of the fire’s flame area:

26 The number of recorded airtanker fires (2,112) is much larger than the number of fires for which I have service process data (581). I have not yet determined why this is the case, but I suspect it is because of the number of airtanker fires that are fought by Twin Otters, the number of fires that are fought by borrowed airtankers from other provincial agencies, and the fact that I omitted airtanker trip data for when multiple fires were fought on a single trip.

27 Flame area is equal to the fire’s perimeter, $P$, multiplied by the flame height. I made a simplifying assumption that the flame height is roughly proportional to fire intensity and can be approximated by the square root of the FWI. Therefore I assume that a surrogate index of the flame area is proportional to the perimeter multiplied by the square root of the FWI. By assuming that fires are circular, the perimeter can be approximated as $2\sqrt{\pi A}$, where $A$ is the
\[ \text{Logit}(Y) = \beta_0 + \beta_1 \text{FlameArea} \]

A summary of the results are shown in Table 6. The C-statistic indicates that the model provides a reasonable fit to the data. A plot of the fitted logistic curve can be found in Figure 20.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Parameter Estimate</th>
<th>Standard Error</th>
<th>( p )</th>
<th>C-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant (( \beta_0 ))</td>
<td>-1.2786</td>
<td>0.0497</td>
<td>&lt;0.001</td>
<td>0.673</td>
</tr>
<tr>
<td>Flame Area (( \beta_1 ))</td>
<td>0.1062</td>
<td>0.0066</td>
<td>&lt;0.001</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Results of the logistic regression model to predict the probability of dispatching 1 or more airtankers to a fire (n=4846).

In addition to the fitted model, an empirical dispatch probability model was also developed. The data was summarized into deciles, which each represent 1/10\(^{th}\) of the total population. For each decile, an empirical estimate of the dispatch probability was calculated. These empirical estimates are shown in Figure 20 and are plotted against each decile’s median flame area index.

size of the fire when it is first reported. The flame height is also assumed to be constant around the fire. There may be another scale on which the FWI is measured that may be more appropriate for this analysis.
Figure 20: Empirical and fitted dispatching probabilities as a function of a flame area index (in hundreds of meters squared). The empirical and fitted models are represented by the set of discrete points and the continuous curve, respectively.

It is important to note the distinction between fires that ‘require’ airtanker suppression and fires that ‘receive’ airtanker suppression. If no airtankers are available, then a fire that may ‘require’ an airtanker may only be suppressed by ground resources (e.g., fire fighters). The simple model that I have built considers those fires that received at least one airtanker.

Therefore, when consulting an initial attack airtanker system model, it is important to consider that the simulated service times and response times have been largely influenced by:

1) Where airtankers are deployed at the beginning of the day;
2) How airtankers are redeployed throughout the day as actual and anticipated fire occurrence predictions change;
3) Explicit or implicit dispatch rules.
3.2.5 Summary

To quantify the relationship between service time and the many factors discussed above is very difficult because of the complexity of the initial attack airtanker system. Many of these factors are interrelated, which makes it difficult to quantify the relationship between service time and any individual factor. In other words, the service time is in fact a complex function of the state of the system, which can and does change over time. Factors that define the state of the system include: the spatial distribution and arrival rate of fires; the number of airports used for dispatching, and their location in the response area relative to other airports; the number of airtankers at each airport; the status of each airtanker upon report of a new fire (busy/available); the deployment/dispatching policy; and the pilot alert status.

To circumvent these issues, I attempt to model some components of the airtanker service process that can be incorporated in simple simulation models of the initial attack airtanker system and produce reliable results.

3.3 Service Process Models

There is a discussion in chapter 2 that describes how service process information is extracted from the Aircraft Tracking System (ATS) and Daily Fire Operations Support System (DFOSS) databases using a novel fire matching procedure and a pattern recognition algorithm for identifying key events during an airtanker's trip. This information was stored in the Airtanker Service Process (ASP) database, which was subsequently used to calculate the following:

\[ T_{BF} = OS_A - S_B \]
\[ T_{FB} = S_E - OS_D \]
\[ t_{drop}^i = T_{i+1} - T_i, \quad i = 1, 2, \ldots, N_{drop} - 1 \]

where \( T_{BF} \) is the base-to-fire travel time, \( OS_A \) is the on-scene arrival time, \( S_B \) is the time service begins, \( T_{FB} \) is the fire-to-base travel time, \( S_E \) is the time service ends, \( OS_D \) is the on-scene departure time, \( t_{drop}^i \) is the time between the \( i + 1 \) and \( i \)th drop, and \( T_i \) is the time of the \( i \)th drop.
With this data, a number of airtanker service process models were developed and are discussed in the following sections.

3.3.1 Number of Drops per Fire

There are 303 fires in the ASP database that have drop data and were fought by at least one airtanker on the same day or the day after the fire’s report date. Some of these fires were delivered an abnormally large number of drops for initial attack fires (see Figure 21), which suggests that they were extended rather than initial attack fires. As a result, a smaller subset of the drop data was created. All fires that were delivered more than 35 drops of water were removed\(^{28}\), which left 273 fires in the subset (see Figure 22).

\[\text{Figure 21: Histogram of the number of drops per fire.}\]

\(^{28}\) Airtankers are used on both initial attack and extended attack fires. It is not clear, however, when a fire shifts from initial attack to extended attack. Therefore, 35 drops was an arbitrary level that I assumed would only include initial attack fires.
Figure 22: Histogram of the number of drops per fire when the number of drops is less than or equal to 35.

In this section a zero-truncated (ZT) regression model\(^{29}\) is developed to estimate the expected number of water drops delivered to each initial attack fire. Since the number of drops is recorded in discrete units, a ZT negative binomial and ZT Poisson regression models are fitted to the ASP drop data. ZT Poisson and ZT negative binomial regression models assume that the response variable (the number of drops) follows a ZT Poisson and ZT negative binomial distribution, respectively. These models also assume that the natural logarithm of the expected value can be modeled by a linear combination of unknown parameters. I hypothesize that the Fire Weather Index (FWI) and the size of the fire at the time of initial attack (\(Size_{IA}\)) are predictor variables that should be considered for inclusion in both the ZT Poisson and ZT negative binomial regression models. Therefore, my hypothesis is that the number of drops is given by:

\(^{29}\) We selected a zero-truncated model since airtankers deliver at least one drop to each fire.
\[ N_{\text{drops}} \sim ZT \text{Poission}(E[N_{\text{drops}}]) \]

or

\[ N_{\text{drops}} \sim ZT \text{NegBin}(E[N_{\text{drops}}], \theta) \]

where \[ Log_e(E[N_{\text{drops}}]) = \alpha_1 + \alpha_2 \text{FWI} + \alpha_3 \text{Size}_{IA} . \] The results of both models are as follows:

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>Degrees of Freedom</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZT Poisson</td>
<td>-1295</td>
<td>3</td>
<td>2596.02</td>
</tr>
<tr>
<td>ZT negative binomial</td>
<td>-888.1</td>
<td>4</td>
<td>1784.2</td>
</tr>
</tbody>
</table>

ZT Poisson and ZT negative binomial distributions were also fitted to the drop data and are shown in Figure 23.

Figure 23: ZT Poisson and negative binomial distributions fitted to the drop data.
These results indicate that the ZT negative-binomial provides a better fit to the drop data and that the Intercept, FWI, and \( \theta \) estimates are all significant at the 95% level (see Table 7), while the size of the fire at initial attack is not a significant predictor.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Z value</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.1526</td>
<td>0.0850</td>
<td>25.321</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>FWI</td>
<td>0.0146</td>
<td>0.0060</td>
<td>2.443</td>
<td>0.015</td>
</tr>
<tr>
<td>( \log(\theta) )</td>
<td>0.6671</td>
<td>0.1204</td>
<td>5.539</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Table 7: Zero-truncated negative-binomial regression diagnostics.

3.3.2 Travel Time Models

In this section a linear regression model is developed to model three airtanker service processes: 1) the travel time to the fire, \( T_{BF} \); 2) cyclic travel time between the fire and the lake, \( T_{drop} \); and 3) the travel time back to base, \( T_{FB} \). The only predictor of travel time (measured in minutes), \( T \), is assumed to be the distance (measured in kilometers), \( D \).

\[
T = \beta_1 + \beta_2 D + \epsilon
\]

where the error term \( \epsilon \sim N(0, \sigma^2) \). The travel time models used the base-to-fire and fire-to-base distances as predictors for their respective model and the drop time model used the lake-to-fire distance as the only predictor. The fitted models appear in Figure 24, Figure 25 and Figure 26, and the diagnostics appear in Table 8.

<table>
<thead>
<tr>
<th>Service Process</th>
<th>Sample Size</th>
<th>( \beta_1 ) (Standard Error)</th>
<th>( \beta_2 ) (Standard Error)</th>
<th>Residual Standard Error (( \epsilon ))</th>
<th>( R^2 )</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T_{BF} )</td>
<td>701</td>
<td>7.319 (0.439)</td>
<td>0.191 (0.003)</td>
<td>6.212</td>
<td>0.854</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>( T_{drop} )</td>
<td>5,575</td>
<td>1.880 (0.020)</td>
<td>0.356 (0.003)</td>
<td>0.845</td>
<td>0.666</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>( T_{FB} )</td>
<td>701</td>
<td>5.246 (0.457)</td>
<td>0.193 (0.003)</td>
<td>6.463</td>
<td>0.847</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Table 8: Diagnostics of linear regression fit for each airtanker service process.
Figure 24: Travel time as a function of base-to-fire distance with residual and Q-Q plots. The Q-Q plot compares the residual data with the predicted data from a normal distribution. See Table 8 for the fitted equation of the base-to-fire travel time model.
Figure 25: Drop time as a function of lake-to-fire distance with residual and Q-Q plots. The Q-Q plot compares the residual data with the predicted data from a normal distribution. See Table 8 for the fitted equation of the lake-to-fire travel time model.
3.3.3 Average Airtanker Speed

Using the travel time models, the average airtanker speed can be estimated during the three portions of an airtanker’s trip: 1) traveling to the fire, 2) during the drop process, and 3) returning to the base. The travel time models are of the form $E[T] = \beta_1 + \beta_2 D$, therefore the average speed, $\bar{V}$, will in fact be a function of the distance, and can be calculated as follows:

$$\bar{V} = \frac{D}{E[T]} = \frac{D}{\beta_1 + \beta_2 D}$$

where $\beta_1 + \beta_2 D > 0$. For each of the three portions of the trip, the average speed is given by:
where $\alpha$ represents a geometric correction factor\textsuperscript{30}. For the case when the flight path during the drop process is assumed to be circular, the speed profile (shown in Figure 27) indicates that the average speeds for longer distances appear to be too high. This conclusion is drawn from the fact that these speeds are eclipsing the maximum average speeds during the base-to-fire and fire-to-base portions of the trip (see Figure 28). On the other hand, the minimum distance travelled (i.e., the minimum possible average speed) by the airtanker during the drop process is twice the straight line distance between the lake and the fire. In this case, the geometric correction factor is $\alpha = 2$. The true average speed profile likely falls somewhere between the two curves in Figure 27), and the associated flight path would be shaped like an ellipse whose characteristics would depend on the distance between the lake and the fire, and their relative orientation (see Figure 29 and Figure 30 for comparisons of actual flight path with the circular path assumption). The speed profile would likely be similar to the “Circular path” profile over short distances, and converge towards the “Straight path” profile as the lake-to-fire distance increases (see the “Hypothetical” curve in Figure 27). This is because as the distance between the lake and the fire increases, the ellipse-shaped flight path becomes more elongated.

\[ \bar{V}_{BF} = \frac{D_{BF}}{E[T_{BF}]} = \frac{D_{BF}}{7.319 + 0.191D_{BF}} \]

\[ \bar{V}_{\text{drop}} = \alpha \frac{D_{LF}}{E[T_{\text{drop}}]} = \frac{\alpha D_{LF}}{1.880 + 0.356D_{LF}} \]

\[ \bar{V}_{FB} = \frac{D_{FB}}{E[T_{FB}]} = \frac{D_{FB}}{5.246 + 0.193D_{FB}} \]

\textsuperscript{30} In our drop time analysis, we regressed against the one-way straight line distance between the lake and the fire. In reality, however, the airtanker travels much further – if we assume that the airtanker flies in a circular pattern where the lake-to-fire distance represents the diameter of the circle (see Figure 29) then the distance flown is equal to the perimeter of the circle, $P = 2\pi R = \pi D_{LF}$. Therefore, the geometric correction factor in this case is $\alpha = \pi$.  

58
Figure 27: Drop process speed as a function of lake-to-fire distance for straight-line and circular flight path assumptions. Also included is the assumption from Islam et al. (2009) regarding average airtanker speed during the entire portion of the trip.
Figure 28: Speed profiles for base-to-fire and fire-to-base portions of the airtanker’s trip. Also plotted are the average speed assumptions made by Bombardier (Bombardier Website, 2012), the OMNR (Personal Communication, Joe Eder OMNR), and Islam et al. (2009).
Figure 29: Circular flight path assumption overestimates the distance travelled. This figure shows airtanker making drops on KEN 104 between 10:00 pm GMT and 11:00 pm GMT on August 23, 2011.
3.3.4 On-scene Time Model

Recall that the on-scene time is equal to the number of drops multiplied by the average drop time. The models developed in this chapter for predicting the number of drops and the average drop time could be used to estimate the on-scene time in the following way. Suppose I want to estimate the on-scene time for a fire that has been assigned 2 airtankers for initial attack. First, I estimate the required number of drops, $N_{req}$, using the number of drops model. Next, I estimate the lake-to-fire distance, $D_{LF}$, using the lake-to-fire distance model, and convert that distance into a drop time, $T_{drop}$, using the drop time model. Since this fire has been assigned two airtankers, the estimated drop time needs to be adjusted - historically when fires are assigned more than one airtanker in simple queueing models, the airtankers are grouped into a single entity that can work proportionally faster during the drop process (e.g., a 2-airtanker entity can deliver drops of water...
twice as fast). So in this case, the true estimated drop time is $\frac{T_{drop}}{2}$. Therefore, the on-scene time can be estimated as follows:

$$T_{OS} = \frac{N_{req} T_{drop}}{2}, \text{ for 2 airtankers}$$

If there were $n$ airtankers assigned to this fire, then the on-scene time can be estimated as:

$$T_{OS} = \frac{N_{req} T_{drop}}{n}, \text{ for } n \text{ airtankers}$$

In reality, however, there are a number of reasons why this estimate of $T_{OS}$ would not be appropriate:

1) Many fires continue to grow as they are being fought by airtankers and other ground suppression resources. $N_{req}$ is never truly known by fire managers since unexpected fire growth patterns and sudden changes in weather may result in a totally different amount of water being dropped than was initially thought to be needed;

2) When multiple airtankers are working on a fire, they may use different lakes to pick up water in order to avoid potential collisions with the other airtankers. As a result, the lake-to-fire distance, and subsequently the drop time may be different for each airtanker, and may require a ‘2nd closest landable lake’ distance model;

3) Occasionally airtankers must wait to drop a load of water onto the fire. This may occur if another airtanker is making a drop on the fire or if there are other fire fighters and/or helicopters that are located within the drop zone.

For these types of reasons, the on-scene time data from the ASP database was used to develop a simple model of the on-scene time that implicitly captures all such variability. Figure 31 shows a histogram of the on-scene time data for all initial attack fires during the study period (2006-2011). I categorized fires as initial attack fires if an airtanker was dispatched on or the day after the fire was reported\textsuperscript{31}. The maximum-likelihood parameter estimation method was used to fit a lognormal distribution to the on-scene time data (see Table 9). To determine the goodness of fit,

\textsuperscript{31} Occasionally fires get reported late at night when it is not safe for pilots to be flying – they are dispatched to the fire the next day to begin initial attack.
a Kolmogorov-Smirnov test was performed. The test results (see Table 9 for KS test results) suggest that the lognormal distribution provides a good fit to the on-scene time data. In addition, the Q-Q plot in Figure 32 shows that a lognormal distribution provides a reasonable fit. I also applied an Anderson-Darling test and found that the null hypothesis that the data follows a lognormal distribution ($p < 0.01$) should be rejected, which suggests that the data does not fit the tails of the lognormal distribution very well.

![Histogram](image)

**Figure 31:** Histogram of the on-scene time with a fitted lognormal distribution.
Figure 32: Q-Q plot comparing the sample on-scene time data with the predicted on-scene time data.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Sample Size</th>
<th>$\mu$ (Standard Error)</th>
<th>$\sigma^2$ (Standard Error)</th>
<th>KS test</th>
<th>AD test</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{os}$</td>
<td>581</td>
<td>3.581 (0.033)</td>
<td>0.772 (0.023)</td>
<td>0.055</td>
<td>2.370</td>
</tr>
</tbody>
</table>

Table 9: Lognormal parameter estimates.

3.3.5 Service Time Model

When fire managers try to evaluate and schedule their resource requirements over an entire fire season, there is tremendous uncertainty regarding the service time and how it depends on a number of factors. One way to deal with these uncertainties is to develop an unconditional service time model that implicitly captures the natural variability of the system. This service time distribution can be used in a simple IAAS queueing model (e.g., $M/G/s$) to predict the system’s performance under the assumption that a future system will behave like it has in the past.
I followed the recommendations of Fortin (1989) and fit an Erlang distribution to the ASP service time data using a maximum-likelihood parameter estimation method. The results indicated that the data best fit an Erlang distribution with shape and scale parameters of 3 and 0.025, respectively (see Figure 33). However, the Q-Q plot in Figure 34 indicates that the Erlang distribution does not provide a very good fit to the service time data. In fact, the KS goodness-of-fit test (Massey 1951) was performed and the results indicated that the null hypothesis that the data follows an Erlang distribution should be rejected (p-value < 0.01). Instead, a lognormal distribution provided a better fit (see Figure 33). The maximum-likelihood parameter estimation method was used to determine that the data best fit a \( \ln N(\mu = 4.611 (0.021), \sigma^2 = 0.482 (0.015)) \) distribution. The Q-Q plot in Figure 35 indicates that the lognormal distribution provides a better fit to the data, although the model does appear to underestimate the frequency of service times between 180-240 minutes. In addition, the KS test was performed and the results indicated the null hypothesis that the data follows a lognormal distribution should not be rejected because of a large p-value (0.3204). An AD test was also performed and the results indicated that the null hypothesis that the data follows a lognormal distribution should be rejected (p < 0.01), which suggests that the data does not fit the tails of the lognormal distribution very well.
Figure 33: Histogram of service times for initial attack fires with a fitted lognormal distribution and Erlang distribution.

Figure 34: Q-Q plot comparing the sample service time data with the predicted service time data from an Erlang distribution.
Figure 35: Q-Q plot comparing the sample service time data with the predicted service time data from a lognormal distribution.

3.4 Discussion

There has been very little operations research work done to estimate the parameters of service process models in urban emergency response systems, let alone the forest fire initial attack airtanker system. This has primarily been due to the lack of airtanker data available for analysis. After identifying a need for more detailed service process information, I developed a procedure for extracting such information from millions of raw GPS data points and storing the extracted data into what I called the Airtanker Service Process database.

This previously unavailable data was used to develop a number of detailed service process models (see Table 10). I developed models that can be used to estimate the base-to-fire and lake-to-fire distances if the location of the fire is unknown. These distance estimates can be used as inputs for the travel time models that can predict the airtanker drop time and flying time to and from the fire. The travel time to and from the fire depends on the base-to-fire and fire-to-base distances, respectively, which I suspect are very similar to the actual distance travelled by the aircraft. The drop time model, on the other hand, regresses the cycle time against the straight line
distance between the lake and the fire, which I assume was proportional to the actual distance flown by the aircraft.

<table>
<thead>
<tr>
<th>Service Process</th>
<th>Statistical Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service time ($S$)</td>
<td>$\ln N(\mu = 4.611, \sigma^2 = 0.482)$</td>
</tr>
<tr>
<td>Base-to-fire travel time ($T_{BF}$)</td>
<td>$7.319 + 0.191D_{BF} + \epsilon$, $\epsilon \sim N(0, 0.212)$</td>
</tr>
<tr>
<td>On-scene firefighting time ($T_{OS}$)</td>
<td>$\ln N(\mu = 3.581, \sigma^2 = 0.772)$</td>
</tr>
<tr>
<td>Fire-to-base travel time ($T_{FB}$)</td>
<td>$5.246 + 0.193D_{FB} + \epsilon$, $\epsilon \sim N(0, 0.463)$</td>
</tr>
<tr>
<td>Number of drops ($N_{drops}$)</td>
<td>$ZTNegBin(E[N_{drops}] = 8.602 + e^{0.015FWI}, \theta = 1.949)$</td>
</tr>
<tr>
<td>Drop time ($T_{drop}$)</td>
<td>$1.880 + 0.356D_{LF} + \epsilon$, $\epsilon \sim N(0, 0.845)$</td>
</tr>
</tbody>
</table>

Other Measures of Interest

<table>
<thead>
<tr>
<th>Service Process</th>
<th>Statistical Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base-to-fire distance ($D_{BF}$)</td>
<td>$\ln N(\mu = 4.638, \sigma^2 = 0.751)$</td>
</tr>
<tr>
<td>Lake-to-fire distance ($D_{LF}$)</td>
<td>$\ln N(\mu = 1.466, \sigma^2 = 0.703)$</td>
</tr>
<tr>
<td>Airtanker Dispatch Probability</td>
<td>$\frac{1}{1 + 3.60e^{-0.11 FlameArea}}$</td>
</tr>
</tbody>
</table>

Table 10: Service process models that were developed and described in Chapter 3.

It was assumed that the travel time (to and from the fire) and drop time could both be modelled using linear regression models that use distance as a predictor. Each of the two processes is believed to contain a fixed portion of time that is common to each observation, and a portion of time that is proportional to the distance travelled. For instance, the travel time to the fire includes the time for pilots to prepare for takeoff and taxi the airtanker to the end of the runway. These events are common to all airtanker trips and are assumed to be fixed. The distance flown, however, will vary from trip to trip depending on the location of the fire and the airtanker's home base. Likewise, the drop time model also includes a fixed time component: the time required for the airtanker to scoop up water from the lake. This will depend on the capacity of the reservoir and how quickly water is captured, but since the same type of aircraft is being modelled, then this time to scoop should be similar for each pickup of water.

Despite the results of my models, airtankers do not travel at constant speeds throughout their trip. Airtanker speed is particularly variable during the drop process, which is shown in Figure 5. The maximum speed achieved during the drop process depends on the lake-to-fire distance because the distance will determine how much an airtanker can accelerate before it must either make a
drop or a pickup of water. It appears that for all distances greater than some threshold distance, the airtanker travel time is equally sensitive to changes in distance because the airtanker has enough time to reach its cruising speed. This may explain why the data appears less noisy for longer lake-to-fire distances.

Factors like the pilot’s experience and local weather conditions may also have an effect on the travel time and drop time. Wind speeds in particular are likely to have an effect on my travel time model since travel times to and from the fire may vary significantly if an airtanker is travelling directly into/with a strong wind. From Figure 24, Figure 25 and Figure 26, there are a number of data points that are not represented well by the fitted travel time models. These anomalous points tell us about some of the uncertainties in aircraft behaviour on or around fires.

Sometimes when an airtanker is dispatched to a fire, the pilot may be called off the fire and redirected towards another higher priority fire. In addition, the air attack officer may not have been able to find the fire and subsequently cannot direct the pilot (this is usually a consequence of a mis-reported fire). Occasionally, pilots are directed by the air attack officer to circle in the air and wait to initiate suppression actions because the drop area had not yet been cleared of firefighters, equipment, resources, and/or helicopters. I have seen a number of instances in the data where a drop time differed significantly from the mean drop time during that trip. Unfortunately my algorithms were not designed to detect these anomalous events. Instead I calculated the mean drop time during each trip in which a fire was being fought, and filtered out those drop times that were larger than two standard deviations from the mean. This filter removed 272 drop times from a set of 5,847 (≈ 4.7 %), leaving a total of 5,575 drop times.

The frequency at which GPS units record data has also limited the accuracy of my models – particularly the drop time model. This is because the interval length (30 seconds, 1 minute, or 2 minutes) forced us to approximate when important events have occurred (e.g., a pickup of water, when airtanker arrives on scene of the fire).

The service time is composed of the total travel time and on-scene time, which is subsequently composed of a series of drop times. It is important, therefore, that there is a reliable method for accurately predicting airtanker travel times and drop times. By creating data-driven models of airtanker service processes that can easily be implemented into decision support systems, fire
managers can make more informed decisions regarding the scheduling, deployment and redeployment of airtankers to airports.
Chapter 4: Illustrating the Use of Airtanker Service Process Models: Using Simulation Models to Evaluate Daily Redeployment Strategies

4.1 Introduction

Amphibious waterbombers, also referred to as airtankers, are used for forest fire fighting in several provinces across Canada, including Ontario. In Ontario, forest fires are reported to the Aviation Forest Fire and Emergency Services (AFFES) branch of the Ontario Ministry of Natural Resources (OMNR). Upon receiving a report of a forest fire, the duty officer must decide what suppression resources should be dispatched to that fire. The initial attack team could consist of one or more three to five person ground crews (ranger crews), one or more airtankers, or a combination of both types of resources. The duty officer must consider the risk of not sending enough resources to contain the fire, and having too few resources on reserve for subsequent fires that may or may not be reported later during the day. Typically, fire managers consider a number of factors before making a dispatch decision. These factors include the fire’s fuel type, rate of spread, intensity, and size (McAlpine and Hirsch 1999). If a fire requires airtanker suppression action and there is an airtanker, then the airtanker is dispatched to the fire. The airtanker flies out to the fire, scoops up water from a nearby lake or river and flies back to the fire to drop its load of water, which may or may not be augmented by foam, on the fire. The airtanker continues to make drops by cycling between the lake and the fire until the air attack officer, who supervises the air attack operations and is seated in another aircraft, decides that no further drops are required. At this point, the airtanker returns to its base or is dispatched to another fire.

These airtanker trip events can be aggregated into the airtanker service processes, which are characterized by: the number of water drops on a fire; the on-scene firefighting time; the service time of the fire; the flying time between the airport and the fire, the fire and the lake from which the airtanker picked up water to drop on the fire, and the fire and the airport. In Chapter 3, I discussed how I developed each of my service process models. The purpose of this chapter is to illustrate how these service process models can be used to help solve a complex airtanker fire management decision-making problem.
In this chapter, I first describe the development of a simple discrete-event simulation model of forest fire initial attack airtanker operations. A number of other simulation models of the initial attack airtanker system (IAAS) have been developed in the past (e.g., Simard 1979, Martell et al. 1984, Martell and Tithecott 1991, Islam and Martell 1998) to simulate initial attack airtanker operations under a variety of conditions and scenarios (e.g., various airtanker fleet sizes, home-basing strategies, expected fire loads). Simulation models are a cost-effective alternative for their users to test ‘what-if’ scenarios and resolve complex decision-making problems that are not amenable to analysis using mathematical programming or other optimization methods.

Next, the service process models from chapter 3 are incorporated into my IAAS simulation model to show how this system of models can be used to resolve redeployment decision-making problems, namely the redeployment of airtankers. The question I investigate is whether airtankers should return to their home base or to the closest base once the pilots have completed their firefighting duties on each fire.

The following sections contain a discussion of the development and basic structure of the simulation model and the performance measures used to study the impact of various redeployment strategies.

4.2 Basic Structure of the Simulation Model

4.2.1 Fire Arrival Process

Canadian forest fires are either caused by people or lightning. People-caused fires usually occur at or near recreational sites, along highways and railways, industrial sites (e.g., forest harvesting operations) and at other locations that are close to populated areas. Lightning-caused fires, however, occur relatively uniformly across the landscape and are often discovered by detection patrol aircraft in remote areas.

The development and use of fire occurrence prediction and detection processes is beyond the scope of this thesis so a simple approach was used to model the occurrence of airtanker fires on a landscape of fixed size. A portion of the West Fire Region of Ontario (see Figure 36), which measures 450 km x 300 km in size, was selected and contains the following five airports where airtankers are typically deployed: Red Lake, Kenora, Dryden, Pickle Lake, and Thunder Bay.
Fires are generated according to a non-stationary Poisson process, where the fire arrival rate (expected number of fires per hour per 135,000 km²), \( \lambda(t) \), varies with time throughout the day. The fire arrival rate was assumed to be relatively low at the beginning of each day (7:00 am) and steadily increase every two hours until 3:00 pm when it begins to decrease every two hours until 9:00 pm (see Table 11).

<table>
<thead>
<tr>
<th>Period</th>
<th>Start Time</th>
<th>End Time</th>
<th>( \lambda(t) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7:00 am</td>
<td>9:00 am</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
<td>9:00 am</td>
<td>11:00 am</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>11:00 am</td>
<td>1:00 pm</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>1:00 pm</td>
<td>3:00 pm</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>3:00 pm</td>
<td>5:00 pm</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>5:00 pm</td>
<td>7:00 pm</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>7:00 pm</td>
<td>9:00 pm</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 11: Fire arrival rate table.

It follows from Table 11 that the expected daily fire load (DFL) is 20 fires. To test alternative fire load scenarios, the arrival rate during each period is multiplied by common factor. For example, if a daily fire load of 30 fires is desired, the fire arrival rate during each period should be multiplied by 1.5. Once each fire is created in the model, it is assigned \((x, y)\) coordinates on the 450 km \( \times \) 300 km grid. For the purpose of this thesis, fires are assumed to be uniformly distributed across the grid (i.e., \( x \sim U(0,450) \) and \( y \sim U(0,300) \)).
I also assume that one and only one airtanker is dispatched to each fire, which is not always the case in the real IAAS. Deciding how many airtankers to dispatch to a fire is a complex decision-making problem that has been discussed previously, and to include an intelligent dispatching module in the simulation model is beyond the scope of this thesis.

4.2.2 Airtanker Dispatch Process with Queueing of Fires

After a fire arrives in the IAAS, one of the following events occurs:

1) If there is at least 1 airtanker available\textsuperscript{32}, then the closest available airtanker will be dispatched to the fire.

2) If no airtanker is available, then the fire is placed into an initial attack fire queue of infinite capacity\textsuperscript{33}. Fires in the queue are served on a first-come first-served (FCFS) basis by airtankers as they become available\textsuperscript{34}.

\textsuperscript{32} Airtanker is ‘busy’ if the airtanker is already assigned to a fire, and is ‘available’ otherwise.

\textsuperscript{33} The initial attack fire queue has infinite capacity because in reality all fires in the response area must be served.

\textsuperscript{34} The study area is small enough that all fires would be within the striking range of all airtanker bases.
Each fire is assumed to require only one airtanker for initial attack. It was also assumed that airtankers are never sent directly from one fire to another. As a result, airtankers always return to an airport to refuel before being dispatched to another fire.

The dispatching procedure is modelled as follows: once a fire arrives in the system, and is assigned coordinates \((x_f, y_f)\), the system looks for the nearest available airtanker. To keep track of the availability of each airtanker, I define a binary variable, \(\text{AvailAT}_i\), to be 1 if airtanker \(i\) is available, and 0 if it is currently serving another fire. Upon identifying which airtankers are available, the system must determine which airtanker is the closest to the fire. To do this, simple straight line distance calculations are performed\(^{35}\). For instance, let \(A\) be the set of all available airtankers and suppose airtanker \(i \in A\) has coordinates \((x_i, y_i)\). Then the distance between the fire at \(x_f, y_f\) and each available airtanker is given by the following:

\[
d_{f,i} = \sqrt{(x_f - x_i)^2 + (y_f - y_i)^2} \quad \forall \quad i \in A
\]

Therefore, the distance of the closest available airtanker is given by \(\text{ClosestDist} = \min_{i \in A} d_{f,i}\). If no airtankers are available when a fire arrives in the system, then as soon as an airtanker becomes available, it will immediately be dispatched to that fire.

4.2.3 Airtanker Service Processes

The service time of a fire, \(S\), can be modelled at different levels of detail. The simplest is to use my service time model, which represents the service time as \(S \sim \ln N(\mu = 4.611, \sigma^2 = 0.482)\). This method is more suited to calculate the service time in a simple queueing model since there are no explicit spatial characteristics to be considered.

A more detailed method would be to partition the service time into three components: 1) the travel time to the fire, 2) the on-scene firefighting time, and 3) the travel time back to base. Once a fire arrives in the system and has been assigned the closest available airtanker, the model calculates the bearing from the airport from which the airtanker has been dispatched to the fire, so that it can tell the airtanker which direction it must travel to arrive at that fire.

\(^{35}\) I was unable to use the Haversine formula (Equation 1) for distance calculations since the simulation software I used to model the IAAS, Simio (Pegden 2007), does not currently support the use of latitudes and longitudes.
Next, the base-to-fire distance is converted to a travel time using my base-to-fire travel time model, which is given by \( T_{BF} = 7.319 + 0.191D_{BF} + \epsilon_{BF} \), where \( D_{BF} \) is the base-to-fire distance and \( \epsilon_{BF} \) is the standard error of the base-to-fire travel time model (\( \epsilon_{BF} \sim N(\mu = 0, \sigma^2 = 6.212) \)). Using this travel time, the system estimates the airtanker’s travel speed as \( V = \frac{D_{BF}}{T_{BF}} \). The speed is estimated in this way because it is a function of the distance, which was discussed in section 3.3.3 and seen in Figure 28. Once these calculations are completed, the bearing, speed and travel time are assigned to the airtanker so that it can fly at the appropriate speed and in a direct line to the fire.

When the airtanker arrives at the fire, it begins suppression action. The firefighting time is calculated using the results of my on-scene time model, which is given by \( T_{OS} \sim \ln N(\mu = 3.581, \sigma^2 = 0.772) \).

Finally, the airtanker travels back to a base once it completes its firefighting duties. The time it takes to fly back to a base is determined by the fire-to-base travel time model, which is given by \( T_{FB} = 5.246 + 0.193D_{FB} + \epsilon_{FB} \), where \( \epsilon_{FB} \sim N(\mu = 0, \sigma^2 = 6.463) \), and the airtanker speed is given by \( V = \frac{D_{FB}}{T_{FB}} \). Once the airtanker arrives back at a base, it immediately becomes available for dispatch to another fire.

The most detailed service time model treats the on-scene firefighting time as a series of drop times. I first generate a lake-to-fire distance, which is given by \( D_{LF} \sim \ln N(\mu = 1.466, \sigma^2 = 0.703) \). Next, the distance is converted into a drop time using the drop time model (\( T_{drop} = 1.88 + 0.356D_{LF} + \epsilon_{drop} \), where \( \epsilon_{drop} \sim N(\mu = 0, \sigma^2 = 0.845) \)). The drop time is multiplied by the number of drops to obtain an estimate of the on-scene time. The number of drops can be estimated using the number of drops model, which is given by \( N_{drops} \sim ZTNegBin(8.671 + e^{0.014FW1}, 0.667) \).

4.2.4 Evaluation of IAAS Performance

The simulation model that was developed can be used to help determine whether airtankers should return to their home base or the closest base after fighting each fire to which they are dispatched. The performance of each policy is based on the airtanker response time, the time
between when the fire was first reported and when an airtanker arrives on-scene at the fire. The response time is an important measure of initial attack airtanker system performance because it is a measure of how long fires are expected to wait for an airtanker to be dispatched and the total distance being travelled by airtankers, which is a reflection of how well a deployment strategy is performing. Minimizing or reducing the response time is very important to fire managers because fires continue to grow in size as they wait for an airtanker to begin suppression action. Larger fires tend to be more difficult to contain, so in most cases, fire managers would like to begin suppressing the fire as quickly as possible.

4.3 Model Overview

At the beginning of each simulation run, one airtanker is deployed at each of the five bases across the West Fire Region (WFR) of Ontario (see Figure 37). The simulation starts at 7:00 am and ends 14 hours later at 9:00 pm. When a fire arrives randomly into the system, the closest available airtanker is dispatched to it. If no airtanker is available, the fire is placed in the initial attack queue. As soon as an airtanker becomes available, it is dispatched to the first fire in the queue. The model was developed using Simio simulation software (Pegden 2007) and 10,000 replications were performed.

The service time of fires in the simulation model was partitioned into the three service processes previously discussed (travel time to the fire, on-scene time, travel time back to base). I was unable to incorporate my most detailed service time model in the simulation model since Simio does not currently support the use of zero-truncated distributions.

4.4 Results

The simulation model of the initial attack airtanker system was used to investigate the effect of redeploying airtankers to the closest base instead of their “home” base (for that particular day) upon the completion of their fighting of each fire to which they are dispatched. Fires were assumed to be uniformly distributed across the simulated response area, and their arrival rates were assumed to vary throughout the day according to Table 11. The expected daily fire loads

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36 Good deployment and redeployment strategies are able pre-position and re-position airtankers such that the response time is reduced.
that were experimented with are 20 and 30 fires. It was also assumed that airtankers could only be dispatched to fires before 7:30 pm since the ASP data indicates that 95% of airtankers are dispatched to fires before 7:30 pm. Any unfought fires were left in the system at the end of each run, and in real-life would be fought by initial attack crews the following day. The following results are based on 10,000 single-day replications of each fire load/redeployment scenario.

![Map of West Fire Region with airports marked]

Figure 37: Initial deployment of airtankers at airports in the West Fire Region.

The average response time for each of the two policies was estimated during each of the 14 one-hour time periods. Figure 38 shows the average response time for each redeployment strategy and each daily fire load scenario. Each average response time curve increases until about 3:30 pm, when the average response time reaches its maximum. Following this peak, the average response time decreases until 7:30 pm (after which airtankers are no longer dispatched to fires).

For each daily fire load scenario, the Mann-Whitney U test determined that the response times were significantly shorter when the closest base redeployment strategy was implemented (see Table 12). When the DFL=20, the closest base strategy improves the average response time by 7.2 minutes and is able to serve an additional 0.45 fires on average before the end of the day. When the DFL=30, the closest base strategy improves the average response time by 11.4 minutes and is able to serve an additional 2.24 fires on average before the end of the day.
Figure 38: Average response time (hr.) to fires that arrive at various times of the day, for two fire load scenarios (20, 30 fires/day) and two redeployment strategies (home base, closest base).

Table 12: Mann-Whitney U test to determine if the response time data was significantly different between redeployment strategies for two different fire load scenarios.
4.5 Discussion

A simulation model was developed and used to test whether the response time to fires was significantly different between two redeployment strategies, namely, where airtankers return to their home base versus the base that is closest to the fire which they just finished serving. The results indicated that the closest base redeployment strategy significantly improves the response times to fires.

At the beginning of each day, it was assumed that there were no fires in the system\(^{37}\) - this is when response times tend to be shorter since the system is free of congestion. As the day progresses, however, fires arrive randomly into the system in which there are a finite number of airtankers. For some fire load scenarios, there may not be enough airtankers to respond to each fire immediately – this is why there is an increase in the average response time as the day progresses. Eventually, the average response time begins to decrease as more airtankers become available to respond to fires.

In a real IAAS, the redeployment of airtankers is much more complicated. Airtankers are sometimes sent directly from one fire to another, and will not return back to a base until they must do so to refuel or they are directed to do so by an air attack officer. Here, I have assumed that airtankers return back to a base immediately after they have completed work on a fire. Airtankers may also be redeployed from one airport to another in anticipation of another fire yet to be reported in the area. My focus has been on deciding which base the airtanker should return to once it has completed its duties.

It would be very difficult to use real initial attack airtanker system performance data (e.g., response time) to validate this simulation model. In reality, the response time is a function of the state of the IAAS, which can and does vary over the course of a day. My hypothesis is that the state of the IAAS can be characterized by how many airtankers are available to be dispatched, the number and type of other suppression resources available to be dispatched, the dispatch strategy (e.g., priority dispatching, FIFO), the deployment and redeployment strategies, the expected number of fires yet to be reported and the pilot alert status. It was beyond the scope of

\(^{37}\) In reality, there may be initial attack fires left over from the night before because there are night-time flying restrictions on airtanker operations.
this thesis to categorize the real response time data by the state of the IAAS. The state of the simulated IAAS at each simulated time can be determined, but it would characterize an unrealistic system that is driven by a number of simplified processes. Therefore, it would be unreasonable to compare the real response time data with the simulated response time data.
Chapter 5: Conclusions and Areas for Future Research

For forest fire management agencies like the AFFES branch of the OMNR, tracking their resources, equipment, crews, aircraft, helicopters, and response vehicles in real-time is becoming much easier now that GPS technology is more readily available and financially accessible. I believe that the implementation of GPS tracking devices serves two purposes: 1) fire managers can make more informed deployment and dispatching decisions based on the current levels of crew, aircraft, and helicopter availability in the response region since they can quickly and easily determine the real-time location of each of these resources; and 2) archived GPS data can be used to develop detailed models of airtankers, helicopters and other response vehicle operations that could not have been developed in the past due to the lack of available data.

Chapter 2 contains a discussion of a new method that was developed for using historical fire report data and airtanker GPS data to determine which airtankers were fighting which fires during which trip. A novel pattern recognition algorithm was also developed, which identified when and where loads of water were being picked up by airtankers and delivered to fires. The focus of this thesis was to extract information from airtanker trips where only one fire was fought. Future research should be devoted to developing an enhanced procedure that can extract service process information for multiple fires that are fought by the same airtanker on the same trip. Extracting the distance between subsequent fires would be of interest to airtanker system planners who must consider the fire-to-fire dispatching on a daily basis, especially during periods of extreme fire activity. It would also provide a means of validating the theoretical models of flight distance between concurrent fires developed by Greulich (2005,2008). Another suggestion for future research is to refine the fire matching and water pickup algorithms in order to identify and summarize additional airtanker events which I was not aware of at the time of creating these algorithms. Additional airtanker events include but are not limited to: when an airtanker is dispatched to a fire but does not or cannot pick up a load of water; and when an airtanker is circling above a fire, waiting until ground crews and/or helicopters clear the drop zone before making a drop.

This study focused on the development of a method to extract detailed airtanker trip information from ATS data. This method was only applied to ATS data for airtankers owned by the Ontario
Ministry of Natural Resources; other fire management agencies that own CL-415s and record their real-time location could also benefit from applying my novel pattern recognition algorithms and fire matching procedures. In addition to applying these methods to ATS data from other agencies, the methods could be altered to extract detailed service process information from the GPS data that records the real-time location of other types of aircraft (e.g., Twin Otters and helicopters).

Another suggestion for future research is to refine the list of factors that affect the performance of the initial attack airtanker system, and develop a method to characterize the state of the initial attack airtanker system at any point during the day. This type of information would help all fire managers analyze the effectiveness of their dispatch and deployment decisions and allow them to compare how strong their decision-making abilities are with other fire managers.

In Chapter 3, I described the development of a number of service process models that can be used to: model airtanker travel time to and from the fire; the cycle time between the fire and the lake; the number of water drops delivered to the fire; the on-scene firefighting time; and the service time. These models were part of a preliminary study that focussed on analyzing airtanker service process data. Future research should focus on enhancing these models. For example, a model that considers the effect of wind direction and speed on the airtanker travel time would enhance my travel time model. It may also be of interest to study how the position and orientation of lakes relative to the fire affects the drop time and the shape of the airtanker’s flight path. In addition, future research should investigate whether an unbalanced mixed-effects model for repeated drop time measurements on each fire is more appropriate than the simple fixed-effects drop time model that was developed and discussed in section 3.3.2.

With these service process models, the service time of a fire can be estimated at three levels of detail. The least detailed method is to use my simple service time model which implicitly accounts for several factors that affect the service time of a fire including the fire’s characteristics (e.g., fire size, spread rate, intensity and fuel type), the weather conditions, the distance between the airport and the fire, the distance between the fire and the nearest landable lake, and the dispatch and deployment strategies. It is recommended that my service time model’s use be restricted to simple queueing models of airtanker operations. Future research
should focus on developing a service time model that explicitly accounts for the many factors that affect the service time.

A more detailed method for estimating the service time could be developed by first generating a base-to-fire and fire-to-base distance and converting each of them into a travel time using my travel time models. The on-scene firefighting time can be estimated using my on-scene time model, which implicitly accounts for the factors that affect the on-scene time of a fire, including the fire’s characteristics, the weather conditions, the lake-to-fire distance, and the number of airtankers working on the fire. Predicting the service time of fires using this method would be best suited for a simulation model or a more robust queueing model of airtanker operations.

The most detailed method uses the travel time models for estimating the total travel time and breaks down the on-scene time into a series of drop times. First, a lake-to-fire distance is generated and converted into an average drop time using my drop time model. Next, the number of drops delivered to the fire is estimated using my number of drops model. The on-scene time can therefore be estimated as the average drop time multiplied by the number of drops delivered to the fire. This method offers flexibility for calculating the on-scene time when there are multiple airtankers working on the same fire – the number of drops can be distributed evenly amongst the airtankers, which each scoop water either from the same lake or a different nearby lake. It is recommended that this method be used in more detailed simulation models of airtanker operations that support zero-truncated distributions.

In Chapter 4, I discussed the development of a discrete-event simulation model of the initial attack airtanker system in Ontario that can incorporate my service process models to help evaluate alternative policies and strategies. In particular, I looked at whether returning airtankers to the closest base versus their home base upon completion of the serving of a fire would improve the average response time to fires that are distributed uniformly across the landscape, and follow a non-stationary Poisson arrival process with rates that vary throughout the day. The results indicated that the closest base redeployment strategy significantly improved the response time to fires. Future research should focus on determining whether the results of my simulation model can be replicated in a $M(t)/G/\infty$ queueing model, which could be used to identify conditions under which it is or is not appropriate to use an $M(t)/G/\infty$ queueing model to model
an initial attack airtanker system (Fortin 1989).
References


Greulich, F., and Oregan, W., 1975. Allocation model for air tanker initial attack in firefighting. USDA Forest Service Research Note PSW-301.


