Impact of Wind Forecast Errors with Optimal and Suboptimal Generation Redispach Policies

by

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A thesis submitted in conformity with the requirements for the degree of Master of Applied Science
Graduate Department of Electrical and Computer Engineering
University of Toronto

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Abstract

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2016

With increasing environmental concerns and the development of technology, installation of variable generation—wind turbine generators (WTGs) especially—has been increasing dramatically in the past decades. Uncertainty in variable generation accumulates, contributing to the complexity of both operations (such as generation redispatch) and planning of the system. There already exist a variety of optimization methods in the literature emphasizing dispatch among multiple areas, such as fixed participation factor, whereas little has been discussed to regulate generation utilizing detailed generation data within each area. This thesis presents a comparison of three different generation redispatch policies and their impacts on line flows and transmission usage in response to wind forecast errors. The three policies are the participation factor policy, the affine response policy and the bilevel programming (BLP) policy. The policies are tested on multiple systems to illustrate more active network monitoring and control.
Acknowledgements

First and foremost, I would like to express my most sincere gratitude and appreciation to my supervisor, Prof. J. E. Tate of the The Edward S. Rogers Sr. Department of Electrical and Computer Engineering of University of Toronto, for his constant and insightful guidance, invaluable advice and encouragement throughout the entire course of work.

Next, I would like to express my thanks to my thesis committee members: Prof. P. W. Lehn, Prof. A. Prodic, and Prof. J. H. Anderson, for their insights and suggestions.

Last but not least, I would like to express my deepest appreciation to my parents for their most concrete support and understanding during my study.
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Nomenclature

Indices

\( N \) Number of buses with variable generation or load
\( G \) Number of conventional, dispatchable generators
\( L \) Number of monitored transmission lines

Variables

\( w_a \) Actual output for one wind generator
\( w_f \) Forecast output for one wind generator
\( \Delta w_e \) Forecast error in output for one wind generator
\( \Delta \eta \in \mathbb{R}^N \) Net power injection forecast error
\( \Delta g \in \mathbb{R}^G \) Changes in controllable generation dispatch
\( f \in \mathbb{R}^L \) Line flows
\( \Delta f \in \mathbb{R}^L \) Changes in line flows
\( \text{OL} \in \mathbb{R}^L \) Line overload penalty value (objective value in the optimization problem)
\( \beta \in \mathbb{R}^G \) Participation factor matrix in the participation factor policy
\( \gamma \in \mathbb{R}^G \) Constant offset in the participation factor policy
\( C \in \mathbb{R}^{G \times N} \) Line dependence matrix in the affine response policy
\( d \in \mathbb{R}^G \) Constant offset in the affine response policy

Parameters

\( \Psi_N \in \mathbb{R}^{L \times N} \) Injection shift factors for buses with forecast error
\( \Psi_c \in \mathbb{R}^{L \times G} \) Injection shift factors for conventional generators
\( \Delta \eta_{\text{min}}, \Delta \eta_{\text{max}} \in \mathbb{R}^N \) Lower and upper bounds on \( \Delta \eta \)
\( \Delta g_{\text{min}}, \Delta g_{\text{max}} \in \mathbb{R}^G \) Lower and upper bounds on \( \Delta g \)
\( \Delta f_{\text{min}}, \Delta f_{\text{max}} \in \mathbb{R}^L \) Lower and upper bounds on \( \Delta f \)
\( f_{\text{base}} \in \mathbb{R}^L \) Line flows based on forecast conditions
\( f_{\text{rating}} \in \mathbb{R}^L \) Line ratings
\( \Phi \in \mathbb{R}^{L \times L} \) Diagonal matrix of line ratings (i.e., \( \text{diag}(f_{\text{rating}}) \))
Chapter 1

Introduction

1.1 Background and Motivation

Renewable generation has enjoyed a significant growth globally in the past several decades. Penetration of renewable energy continued to increase because of the backdrop of increasing global energy consumption and a dramatic decrease in oil and natural gas prices in the past few years. By the end of 2014, renewables comprised an estimated 27.7% of the world’s power generating capacity, enough to supply an estimated 22.8% of global demand [4]. Renewable energy not only mitigates concerns about global warming, but also creates new economic opportunities and expands energy access to remote districts. The United Nations General Assembly unanimously declared the decade 2014-2024 as the “Decade of Sustainable Energy for All”, underscoring the importance of energy issues for sustainable development and for the elaboration of the post-2015 development agenda [5]. The objectives are to ensure universal access to modern energy services, to double the global rate of improvement in energy efficiency, and to double the share of renewable energy in the global energy mix by 2030 [6].

New investment in renewable power and fuels increases each year and has reached 270 billion USD worldwide in 2014. Most countries have enacted policies to regulate
and promote renewables. As of early 2015, 164 countries have renewable energy targets and renewable energy support policies are available in 145 countries [4]. Among various energy supply policies, Feed-in Tariff (FIT) policies proposed by the National Renewable Energy Laboratory (NREL) have long been the most popular around the world, which provide developers long-term purchase agreements for the sale of electricity generated from renewable energy sources [7]. The government of Ontario launched a FIT in 2009 and announced several changes based on a two-year review of the program in 2012 [8]. The Independent Electricity System Operator (IESO) amends FIT policies regularly to ensure long-term success in Ontario’s electricity sector. There are currently two forms of FIT policies available in Ontario [9]. The FIT Program is aimed for projects with a rated electricity generating capacity greater than 10 kilowatts (kW) and generally up to 500 kW, and the microFIT Program is for projects of 10 kW or less.

Ontario’s electricity generation fleet has transited to a more sustainable supply mix since the market opened in 2002. Renewable generation constituted merely 1.5% of total electricity output in 2008, whereas this rate increased to 6.3% in 2015 [10]. Renewables constitute 11.9% of Ontario’s installed generation capacity as of Mar 22, 2016. As more and more variable generation is installed on the power grid, the impact of uncertainty accumulates and contributes to the complexity of both planning and operations of the transmission system [11].

As with the global trend, the electric power market in Ontario has moved to a deregulated market and the IESO is responsible for operations and planning of Ontario’s electric power industry. Since the IESO is an independent system operator, this deregulation structure alleviates monopoly in the industry and improves economic efficiency. Innovation to deal with variable generation for both operations and planning is of great significance to the IESO.

From the planning perspective, variable generation can lead to large variations in network flows and—due to their placement in sparse and probably remote locations—a
need for transmission upgrades to facilitate these unpredictable flows. Fig. 1.1 shows the locations of wind farms currently installed in Ontario [12].

From the operations perspective, increasing variable generation penetration imposes substantial load following and regulation requirements to manage the inherent uncertainty in the generation output. Among various types of renewable energies, wind power has established widespread penetration in the power grid. An increasing number of WTGs have been installed in the transmission system every year. Such large amount of variable generation (VG) can have huge impacts on the viability of traditional generation dispatch. As in the case of North America, NERC established the Integration of Variable
Generation Task Force (IVGTF) in December 2007 and has published several reports identifying technical considerations on real-time operations associated with integrating high penetrations of VG [13]. Results from IVGTF and other pilot projects addressed the importance of more accurate forecasting and the integration of the forecasting products into actual operations [14], which led to switching from decentralized forecasting—each variable generator is responsible to generate its own forecast data—to centralized forecasting. On November 1, 2011, the Market Rule for Centralized Forecasting came into effect, requiring all wind and solar facilities with 5 MW or larger capacity to register with the IESO for centralized forecasting service. Wind and solar units applicable are required to collect and submit both facility data (static data such as facility location, generating unit location and characteristics) and monitoring data (dynamic data, i.e., operational and meteorological information) to the IESO, which is responsible to implement a centralized forecast for all wind and solar units. Before enforcing central forecasting, wind facilities used different forecasting methods and had different update frequencies, which created higher aggregate forecast errors in comparison to those using a uniform forecasting method and update frequency. Each facility may also use different biases with their forecasts, due to economical incentives. Centralized forecasting produces reliable, consistent and accurate forecasts, and therefore mitigates overall forecast errors. When there is a need for requirements update, it is more cost-effective to upgrade a centralized forecasting system than upgrading individual forecast devices. The procedure for dispatch with centralized forecasting is shown in Fig. 1.2.

Although the IESO institutes a dispatch process for both wind and solar facilities connected to the grid, this dispatch is generally used only when there is surplus baseload generation. Moreover, the IESO will not dispatch wind and solar facilities connected to local distribution systems. The continued presence of controllable generation on the system can help alleviate power flow variations due to variable generation resources.

The IESO currently adopts a two-steps dispatch process, that is, pre-dispatch schedul-
Figure 1.2: Flowchart of operation decisions with central forecasting service

During pre-dispatch scheduling process, forecast variable generation is utilized. During the real-time scheduling process,
actual monitoring data that updates every 30 seconds is utilized. Forecast error is calculated from the difference between the real-time monitoring data and the forecast value from pre-dispatch. Forecast error is then compensated by redispatch based on real-time offer from generators and operating reserves (ORs). If the resultant transmission flows exceed regulation, curtailing and shedding may also be included. The conventional approach to generation redispatch utilizes a fixed participation factor policy and adjusts generator outputs based on the total (net) load imbalance on the system. However, the variations are not limited to historical demand centers any more. In practice, it may be difficult to get enough operating reserves at hand or it may be too expensive to do so. Therefore, the system operator demands more intelligent dispatch methods to cope with increasing variable generation rather than using a conservative deterministic modeling.

An alternative is stochastic programming, which utilizes a predicted scenario and a large number of error scenarios based on an assumed error probability distribution [16]. The computational cost and scenario selection are two major challenges for this framework, and have limited its application in actual utility control centers. The nature of the dispatch problem makes bilevel programming (BLP) another good candidate for the dispatch process. However, the hierarchical structure of bilevel programming indicates that it is very complex and time-consuming to find optimal solutions, which leads to an exploration on alternative optimization methods to replace it. Robust optimization—which allows for explicit consideration of power injection uncertainty—is an attractive alternative [17], since it is computationally tractable and tends to provide conservative solutions that are consistent with other utility practices (e.g., “N-1” reliability requirements). The basic premise of robust optimization is to make the solution of an optimization problem (e.g., minimize transmission loading) robust to variations in the problem parameters (e.g., forecast errors). In this thesis, we examine the performance of two different formulations, i.e., the participation factor approach and the affine response approach.

In addition to exploring different types of uncertainty in power injections on the sys-
tem, the other major contribution of this thesis is to evaluate the performance of different
generation redispatch policies. This can have a substantial effect on the transmission line
flows and, as a result, alter the network components that are likely to become overloaded
beyond their existing capacities.

1.2 Objective and Contribution

This thesis focuses on evaluating the performance of three different generation redispatch
approaches with regards to accommodating variations in wind generation. Alternatively,
the main optimization problem could be interpreted as finding the minimum overloads
that will be present despite an optimal response from the grid operator. Although the case
studies implemented wind variations, the approaches could also be used to accommodate
fluctuations in other types of variable generation and load (referred to as “net power
injection variation”).

In particular, we consider generation redispatch based on 1) participation factors,
2) affine response, 3) optimal reaction. The participation factor approach—also com-
monly referred to as “distributed slack” dispatch—adjusts each controllable generator’s
output in proportion to the total amount of power imbalance within the network. The
affine response approach is a logical extension, in which each controllable generator is
dispatched as an affine response to the localized (zonal or bus) net power injection (i.e.,
variable generation minus load) variation. The third approach—optimal reaction—finds
the optimal dispatch of the system’s controllable generation, as would be achieved via an
optimal power flow solution. This last approach is realized with bilevel programming.

1.3 Thesis Outline

This thesis is divided into five major parts. The first part provides an overview of the
methodology utilized in this thesis, i.e., dc power flow, power flow equations, a brief
description of the objective function, ramp rates, and mathematical model of wind generation forecast errors. The second part provides the optimization models corresponding to the three generation redispatch approaches. This is followed by case studies on small-(37-bus) and medium-sized (118-bus) test systems. Based on the simulation results, we explore the significance and applications of the generation redispatch approaches. Finally, the thesis concludes with recommendations for generation redispatch modeling and avenues for future research.
Chapter 2

Methodology

2.1 Dc Power Flow

To ensure computational tractability, the dc power flow model is used to relate bus power injections to phase angles. Dc power flow is much faster to solve than ac power flow, and, for transmission networks, provides reasonable accuracy. For an N-bus network, with bus 1 designated as the slack/reference bus, the dc power flow equations are

\[
B \begin{bmatrix}
\theta_1 \\
\theta_2 \\
\vdots \\
\theta_N
\end{bmatrix} = \begin{bmatrix}
0 \\
P_2 \\
\vdots \\
P_N
\end{bmatrix} \leftrightarrow B\theta = P, \tag{2.1}
\]

where \( B \in \mathbb{R}^{N \times N} \) is the dc power flow matrix [18], \( \theta_i \) is the voltage phasor angle at bus \( i \), and \( \theta_1 \) is the slack/reference angle (set equal to zero). This equation is obtained by making the following assumptions:

1) The line resistances are negligible, in comparison to line reactances, and can be neglected;
2) The phase angle difference across any transmission line, \( \theta_{ij} = \theta_i - \theta_j \), is small enough
that \( \sin \theta_{ij} \approx \theta_i - \theta_j \) and \( \cos \theta_{ij} \approx 1 \);

3) Magnitude of voltage at each bus is unity, i.e., \(|V_i| \approx 1\) per unit.

## 2.2 Power Flow Equations

Using the dc power flow, we introduce injection shift factors (ISFs) to relate power injections to line flows on the system. With the dc power flow assumptions, the flow on each line \( f_l \) is calculated as:

\[
f_l = \frac{1}{X_l}(\theta_l - \theta_l),
\]

(2.2)

where \( \theta_l \) (\( \theta_l \)) is the angle at the from (to) bus of line \( l \) and \( X_l \) is the reactance of line \( l \).

The relationship between flows on the lines \( f = \begin{bmatrix} f_1 & f_2 & \ldots & f_L \end{bmatrix}^T \) and the power injection vector \( P = \begin{bmatrix} P_1 & P_2 & \ldots & P_N \end{bmatrix}^T \) in matrix form is:

\[
f = X^{-1} \times A \times B^{-1} \times P,
\]

(2.3)

where \( X^{-1} \triangleq \begin{bmatrix} \frac{1}{X_1} & 0 & 0 & \ldots & 0 \\
0 & \frac{1}{X_2} & 0 & \ldots & 0 \\
\vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & \ldots & 0 & \frac{1}{X_L} \end{bmatrix} \), and the incidence matrix \( A \in \mathbb{R}^{L \times N} \) has entries at row \( l \) column \( k \) defined by:

\[
A_{(l,k)} = \begin{cases} 
1 & , k = l_f \\
-1 & , k = l_t \\
0 & , \text{otherwise}
\end{cases}
\]

(2.4)

The inverse reactance matrix \((X^{-1})\), incidence matrix \((A)\), and inverse dc power flow matrix \((B^{-1})\) can be combined to directly relate the flow on each line to the power flow.
injections at each bus through the ISF matrix $\Psi \in \mathbb{R}^{L \times N}$:

$$f = \Psi P.$$  \hspace{1cm} (2.5)

The entry at row $l$, column $k$ of $\Psi$, $\Psi_{(l,k)}$, relates the flow (or change in flow) on a line $l$ to the injection (or change in injection) at bus $k$.

Assume there are altogether $N$ buses in the system. Power injection on these buses are subject to forecast errors (caused by variable generation or demand etc.). The real-time power injection at each bus $i$, $P_i$, is modeled as:

$$P_i = g_i - d_i + \Delta g_i - \Delta d_i, \quad \forall i = 1, 2, \ldots, N,$$  \hspace{1cm} (2.6)

where $g_i$ is the deterministic generation at bus $i$ (forecast or dispatched, depending on the type of generation), $d_i$ is the forecast demand/load, $\Delta d_i$ is the demand/load forecast error, and $\Delta g_i$ is the generation forecast error, which is 0 at buses without variable generation. Buses without forecast errors are equivalent to having zero error.

Define the net power injection forecast error as:

$$\Delta \eta_i \triangleq \Delta g_i - \Delta d_i, \quad \forall i = 1, 2, \ldots, N.$$  \hspace{1cm} (2.7)

Hence, we have

$$P_i = g_i - d_i + \Delta \eta_i, \quad \forall i = 1, 2, \ldots, N.$$  \hspace{1cm} (2.8)

During generation redispatch, dispatch decision ($\Delta g$) compensates for net power injection forecast errors ($\Delta \eta$). The change in line flows after generation redispatch and forecast errors are realized can be separated into two components—change in power injection due to a set of net power injection forecast errors ($\Delta \eta$) and change in power injection from generation redispatch ($\Delta g$). Hence, the change in line flow is quantified with $\Psi_N$ and $\Psi_G$ as:
\[ \Delta f = \Psi_N \Delta \eta + \Psi_G \Delta g. \] (2.9)

And the following equality constraint holds to ensure power balance under the (lossless) dc power flow model:
\[ \sum_{i=1}^{N} \Delta \eta_i + \sum_{j=1}^{G} \Delta g_j = 0, \] (2.10)

or, in matrix form,
\[ 1_{1 \times N} \times \Delta \eta + 1_{1 \times G} \times \Delta g = 0, \text{ with} \]
\[ 1_{1 \times X} \triangleq \begin{bmatrix} 1 & 1 & \ldots & 1 \end{bmatrix} \in \mathbb{R}^{1 \times X}. \] (2.12)

### 2.3 Objective Function

The problem of interest is to determine the minimal line overloads within a network such that forecast demand and variable generation, along with associated forecast errors, can be accommodated.

Percentage line overload for a given line \( l \) is calculated as follows:
\[ OL_l = \begin{cases} 0, & f_l^{\text{min}} \leq f_l \leq f_l^{\text{max}} \\ \frac{f_l^{\text{min}} - f_l}{f_l^{\text{rated}}}, & f_l < f_l^{\text{min}} \\ \frac{f_l^{\text{max}} - f_l}{f_l^{\text{rated}}}, & f_l > f_l^{\text{max}} \end{cases} \] (2.13)

where \( f_l \) is the flow on line \( l \), \( f_l^{\text{max(min)}} \) is the maximum (minimum) flow allowed on line \( l \), and \( f_l^{\text{rated}} \) is the line rating. \( OL_l \) is a convex, piecewise-linear function, as illustrated in Fig. 2.1.

The above convex, piecewise-linear function can be rewritten as:
\[ OL_l = \max \left\{ 0, \frac{f_l - f_l^{\text{max}}}{f_l^{\text{rated}}}, \frac{f_l^{\text{min}} - f_l}{f_l^{\text{rated}}} \right\}. \] (2.14)
Figure 2.1: Convex, piecewise-linear penalty function to model percentage line overload at one line ($OL_i$)

To model the change in line flows due to forecast errors, a dc optimal power flow (DCOPF) is utilized to solve for the optimal generation dispatch using forecast variable generation and demand. There should be no overflows on the operation system at this state. The resultant line flows, $f_{\text{base}}$, are the base (i.e., forecast) flow values.

The lower (upper) bounds of change in line flows, $\Delta f_{\text{min}}$ and $\Delta f_{\text{max}}$, are calculated as:

$$\Delta f_{\text{min}} = f_{\text{min}} - f_{\text{base}} \in \mathbb{R}^L,$$  \hspace{1cm} (2.15)  

$$\Delta f_{\text{max}} = f_{\text{max}} - f_{\text{base}} \in \mathbb{R}^L.$$  \hspace{1cm} (2.16)

For simplicity, we assume the lower (upper) bounds of line flows to be the same as ratings (i.e., $f^{\text{min}}_l = -f^{\text{rated}}_l$ and $f^{\text{max}}_l = f^{\text{rated}}_l$) throughout the remainder of the thesis. Therefore, we have:

$$\Delta f_{\text{min}} = -f^{\text{rated}}_l - f_{\text{base}},$$  \hspace{1cm} (2.17)  

$$\Delta f_{\text{max}} = f^{\text{rated}}_l - f_{\text{base}}.$$  \hspace{1cm} (2.18)

Consequently, percentage line overflow for each line after generation redispatch response to net power injection forecast errors is:
\[ \Delta OL_l = \max \left\{ 0, \frac{\Delta f_l - \Delta f^\text{max}_l}{f^\text{rated}_l}, \frac{\Delta f^\text{min}_l - \Delta f_l}{f^\text{rated}_l} \right\}. \] (2.19)

We define a penalty function \( q(\Delta \eta, \Delta g) \) to model percentage line overflows on the system after generation redispatch. For each line \( l \),

\[ q_l \triangleq \Delta OL_l. \] (2.20)

Our task is to minimize the sum of the percentage line overflows due to net power injection forecast errors (\( \Delta \eta \)).

### 2.4 Ramp Rates

Using a DCOPF with forecast generation and load values, the generation output for controllable generators, \( g_{\text{base}} \), is decided and serves as the base condition. In practice, not only should each generator run below its rated value, which usually defines its maximum/minimum output, it should also be restricted by the rate of increasing/decreasing generation output from contemporary power generation, which is called the ramp up/down rate. For example, a rapid change in temperature or output of thermal units may lead to higher maintenance costs or even failure. Consequently, safe ramp up/down rates are provided by the manufacturer and should be followed strictly during generation redispatch.

Ramping capacity varies with the type of generation. Typical ramp rates for coal-fired units are approximately 2 to 4 MW/minute as illustrated in Table 10 of [19], which are around 1% to 3% of rated capacity/minute, whereas those for current gas turbines are typically 15 to 25 MW/minute but may be as high as 50 MW/minute [20]. Hydro power has even higher ramp rates on average. Typical pumped storage power plants have ramp rates of over 40% of rated capacity/minute [21]. In fact, a hydro unit may reach full capacity within seconds, if not constrained by legal restrictions on water flows [22].
Large nuclear and coal plants, referred to as baseload units, have low ramp rates and usually supply energy following the diurnal demand pattern. For load following, power plants with higher ramp capacities like natural gas or oil plants are utilized [24]. Although hydro generation has fast response as well, it can be restricted by environmental constraints, scheduling practice, and market characteristics [24]. With ramp up/down rates taken into account, the output bounds of generation redispatch are quantified as:

\[ \Delta g_{\text{min}} = \max\{-g_{\text{min}} - g_{\text{base}}, \Delta g_{\text{rampDown}}\}, \]  
\[ \Delta g_{\text{max}} = \min\{g_{\text{max}} - g_{\text{base}}, \Delta g_{\text{rampUp}}\}. \]

If we assume that the maximum/minimum generation outputs are the same as power ratings of the controllable generators, and that the ramp up/down rates are proportional to power ratings, the former equations can be rewritten as:

\[ \Delta g_{\text{min}} = \max\{-g_{\text{rated}} - g_{\text{base}}, -r^T_{\text{rd}}g_{\text{rated}}\}, \]  
\[ \Delta g_{\text{max}} = \min\{g_{\text{rated}} - g_{\text{base}}, r^T_{\text{ru}}g_{\text{rated}}\}. \]

where \( r_{\text{ru}} \in \mathbb{R}^G \) and \( r_{\text{rd}} \in \mathbb{R}^G \) are the coefficient vectors for ramp up/down rates.

As shown in Fig. 1 from [25], VGs can lead to steeper ramps and shorter peaks in system operations. This increases possibility for overloads on the system, which is reflected in dispatch as higher objective values. Therefore, ramp rates can be expected to have a stronger influence on generation redispatch for transmission systems with variable generation installation, and can be alleviated with more investment in operating reserves or transmission line upgrades.
2.5 Mathematical Model of Wind Generation Forecast Error

2.5.1 Time Scale of Wind Generation Forecast

Different time scales are utilized in wind generation forecasting, depending on the goals of application, as summarized in Table 2.1 [1].

<table>
<thead>
<tr>
<th>Time horizon</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very short-term</td>
<td>Less than 30 minutes ahead</td>
</tr>
<tr>
<td>Short-term</td>
<td>30 minutes to 6 hours ahead</td>
</tr>
<tr>
<td>Medium-term</td>
<td>6 hours to 1 day ahead</td>
</tr>
<tr>
<td>Long-term</td>
<td>More than 1 day ahead</td>
</tr>
</tbody>
</table>

Table 2.1: Time-scale Classification for Wind Generation Forecast, adapted from [1]

Since this thesis intends to examine performance of difference generation redispatch measures, the time horizon of interest belongs to the short-term forecasting category.

2.5.2 Short-term Wind Generation Forecast

There exist a wide variety of wind generation forecasting methods for different time scales, depending on the goals of application. Among all of the prediction methods for short-term wind generation, persistence method, the simplest and the most straightforward one, plays an important role. The persistence method is based on the assumptions that the atmosphere is quasi-stationary over a short term, and that the wind generation changes slowly enough so that measured wind generation could be used as forecast wind generation some time ahead. The persistence method can be written as [26]:

\[
\hat{P}(t + T | t) = \frac{1}{T} \sum_{i=0}^{n-1} P(t - i\Delta t),
\]  

(2.25)
where $\hat{P}(t + T|t)$ is the forecast wind generation for time $t + T$ made originally at time $t$, $T$ is the prediction time interval containing $n$ time steps, each of which is $\Delta t$ (i.e., $T = n\Delta t$), and $P(t - i\Delta t)$ is the measured wind generation at time $t - i\Delta t$.

The persistence model is the simplest of all, yet can perform well enough for short-term predictions and is usually used as a reference to assess other advanced methods.

Advanced methods utilize forecast meteorological variables (e.g., wind speed and direction, temperature, pressure and humidity) from various Numerical Weather Prediction (NWP) models and convert them into forecast wind generation. Three alternatives to do so are:

1) Physical approaches, which take physical information about the local terrain into consideration. First of all, physical approaches transfer meteorological variables given at data collection grid points to those at the site via Computational Fluid Dynamics (CFD) or other physical models. The refined data is then used to calculate wind generation based either on theoretical power curves provided by manufacturer or empirically derived power curves. Model Output Statistics (MOS) may also be included to minimize systematic errors caused by NWP.

2) Statistical approaches, which emphasize the relation between historical data of wind generation and historical data of forecast and actual meteorological variables. Statistical approaches include time-series methods such as Autoregressive Moving Average (ARMA), and machine-learning methods such as Neural-Networks (NNs) and Support Vector Machines (SVMs).

3) Combined approaches, which use the results from physical approaches as input variables to statistical approaches.
2.5.3 Distribution of Wind Generation Forecast Errors

Forecast errors of wind power facilities are treated as statistical errors [27]:

\[ w_a = w_f + \Delta w_e, \]  

(2.26)

where \( w_a \) is the actual generation, forecast value component \( w_f \) is used in DCOPF to generate data at initial state, and the forecast error component \( \Delta w_e \) is utilized in the three generation redispatch approaches to calculate the value of objective function (i.e., \( \sum_{l=1}^{L} q_l \)).

Distributions of forecast errors in wind power may differ significantly depending on factors such as prediction methods utilized and time scales considered. Wind power forecast errors are assumed to follow a normal distribution in many studies. There are other patterns that could better represent the distribution, as in the case of [28], where the \( \beta \)-distribution is proposed after looking into the highly skewed characteristics of the distribution. Another study by Hodge et al. recommends the Cauchy distribution after examining forecast error distribution using persistence method for multiple time scales between the 1 minute and 3 hours range [29].

It should be noted that the goal of this thesis is to evaluate different generation redispatch approaches, hence distribution of wind generation forecast errors is assumed available. Dispatch decision-makers can determine a specific forecast confidence level and forecast confidence intervals are generated from given error distribution at the forecast point. Using probabilistic modeling, we can predict optimal dispatch decision for any possible wind forecast error scenario within the confidence interval. Therefore, the overall decision obtained can accommodate any scenario within the confidence interval. At the same time, it can alleviate the reliance on operating reserves.

For instance, Fig. 2.2 illustrates the fitted Cauchy distribution for forecast errors of combined ERCOT data using 15 minute average data for the winter time period
Figure 2.2: Fitted Cauchy distribution for forecast errors of combined ERCOT data using 15 minute average data for the winter time period, with $x_0 = 0.4999$ and $\gamma = 0.0069$ as obtained in [29]. The 90% confidence interval is $\pm 8.7\%$ of total capacity; the 95% confidence interval is $\pm 17.5\%$ of total capacity.

Fig. 2.3 is an illustration of the forecast wind generation, actual wind output and associated confidence interval for one single wind farm.
Figure 2.3: Plot of wind forecast, actual output and associated confidence interval for a single wind farm
Figure 2.4: Illustration of wind generation over two wind farms

Assume there are two wind farms in the system, the forecast outputs of which are 100 MW and 80 MW, respectively. The confidence intervals obtained are (70 MW, 130 MW) and (70 MW, 90 MW), respectively. The rectangular region, as shown in Fig. 2.4, is represented as a set of constraints in dispatch process. Dispatch decision-makers take into account all possible scenarios with forecast error that falls within the rectangular region. If there are altogether $n$ ($n \geq 3$) wind farms connected to the network, the region will be an $n$-dimensional convex polyhedron with $2^n$ vertices. The associated set of constraints is referred to in the robust optimization literature as “box” constraints.
2.5.4 Correlation Analysis of Forecast Errors among Different Wind Facilities

Data from two different regions of the Electric Reliability Council of Texas (ERCOT) in the United States is utilized in this thesis. The dataset used includes actual hourly averaged wind power generation and Short-Term Wind Power Forecast (STWPF) for a rolling historical 48-hour period over the south Houston and the west north regions [30]. The correlation coefficient between forecast errors of the two regions on average is 0.0555. Therefore, forecast errors from different wind facilities are assumed independent throughout the remainder of this thesis.
Chapter 3

Comparison of Generation Dispatch Approaches

3.1 Participation Factor Approach

In a standard power flow solution, only a single slack bus (bus 1, using the convention of (2.1)) is responsible for covering any net surplus/deficiency in network power injection. While this may be appropriate for small power variations—as has historically been the case, when demand was the main source of uncertainty—this method of generation re-dispatch is not necessarily appropriate when a large percentage of power is provided by variable generation resources.

A simple extension to the standard slack bus compensation is to allow multiple generators to respond to forecast errors. The participation factor policy allows all active (committed, dispatchable) generators to compensate for power imbalance on the system. This is utilized in automatic generation control (AGC) for the existing system. Each generator changes its output level weighted by the total net power injection forecast errors. Define $\beta = \begin{bmatrix} \beta_1 & \beta_2 & \ldots & \beta_G \end{bmatrix}^T$ as the vector of participation factors. The relationship between each dispatchable generator and net power injection variation is as follows:
\[ \Delta g_j = \beta_j \left( \sum_{i=1}^{N} \Delta \eta_i \right), \quad \forall j = 1, 2, \ldots, G, \quad (3.1) \]

where \( \Delta \eta_i \) is net power injection forecast error at bus \( i \), as defined in (2.7) [31]. Or, in matrix form,

\[ \Delta \mathbf{g} = \mathbf{\beta} \times \mathbf{1}_{1 \times N} \times \Delta \eta. \quad (3.2) \]

In this thesis, an expanded version of the participation factor algorithm is utilized, where the constant offset, \( \gamma = \begin{bmatrix} \gamma_1 & \gamma_2 & \ldots & \gamma_G \end{bmatrix}^T \), is introduced to increase flexibility of the proportional relationship. Hence,

\[ \Delta g_j = \beta_j \left( \sum_{i=1}^{N} \Delta \eta_i \right) + \gamma_j, \quad \forall j = 1, 2, \ldots, G, \quad (3.3) \]

or, in matrix form,

\[ \Delta \mathbf{g} = \mathbf{\beta} \times \mathbf{1}_{1 \times N} \times \Delta \eta + \gamma. \quad (3.4) \]

Under this dispatch regime, the power balance constraint (2.10) is satisfied by enforcing the following two equality constraints:

\[ \sum_{j=1}^{G} \beta_j = -1, \quad (3.5) \]
\[ \sum_{k=1}^{G} \gamma_k = 0. \quad (3.6) \]

The first constraint ensures that the sum of net change in controllable generation balances the total change in the net power injection forecast variation. The second constraint ensures that change in one controllable generator's nominal output is compensated by the remaining generators' nominal output, so that power balance is maintained. We rewrite the above power balance equations into matrix form:

\[ \mathbf{1}_{1 \times G} \times \mathbf{\beta} = -1, \quad (3.7) \]
\[ \mathbf{1}_{1 \times G} \times \gamma = 0. \quad (3.8) \]
Consequently, the generation redispatch problem under the participation factor policy is mathematically expressed as:

$$\min_{\Delta \eta \in \mathcal{N}} \sum_{l=1}^{L} q_l(\Delta \eta, \Delta g)$$

subject to

$$\begin{cases}
\Delta g = \beta \times 1_{1 \times \mathcal{N}} \times \Delta \eta + \gamma \\
1_{1 \times G} \times \beta = -1 \\
1_{1 \times G} \times \gamma = 0 \\
\Delta g_{\text{min}} \leq \Delta g \leq \Delta g_{\text{max}}
\end{cases}$$

(3.9)

where $q_l(\Delta \eta, \Delta g)$ is the penalty function defined in (2.20), explicitly written as a function of the net power injection forecast errors ($\Delta \eta$) and changes in controllable generation ($\Delta g$); $\mathcal{N}$ represents the domain of possible forecast errors; $\beta$ and $\gamma$ are the participation factor policy parameters; and $\Delta g_{\text{min}}$ and $\Delta g_{\text{max}}$ represent the lower and upper bounds of active dispatchable generation on the system (2.21), (2.22).

The set of net power injection deviations in this study, $\mathcal{N}$, is defined by element-wise upper and lower bounds on the forecast errors at each bus (i.e., $\Delta \eta_{\text{min}} \leq \Delta \eta \leq \Delta \eta_{\text{max}}$) and is obtained from given forecast error distribution and specified confidence level. This representation of the forecast errors (referred to in the robust optimization literature as “box” constraints) allows for the robust complement to be easily derived and solved as a linear program [32].

\[1\] In practice, these bounds would be determined based on a confidence level (e.g., capturing 95% of the forecast error distributions).
3.2 Affine Response Approach

The affine response policy [32] takes the concept of a distributed slack one step further by allowing for greater flexibility in the dispatch of the controllable generation resources. Instead of redispersing the controllable generation based on the total power imbalance on the network, each controllable generation is dispatched based on the individual net power injection variation at each bus [31]. Defining $C \in \mathbb{R}^{G \times N}$ as the coefficient of affine response and $d \in \mathbb{R}^G$ as the constant offset, we have

\[
\Delta g = C \times \Delta \eta + d. \tag{3.11}
\]

The power balance constraint (2.10) is satisfied by enforcing the following two equality constraints:

\[
\sum_{i=1}^{G} C_{(i,j)} = -1, \quad \forall j = 1, 2, \ldots, N, \tag{3.12}
\]

\[
\sum_{k=1}^{G} d_k = 0. \tag{3.13}
\]

where $C_{(i,j)}$ denotes the entry at row $i$ and column $j$ of the matrix $C$. The first constraint ensures that each individual forecast error and its total impact on controllable generators are balanced. The second constraint ensures that change in one controllable generator’s nominal output is compensated by the remaining generators’ nominal output, so that power balance is maintained.

The above power balance equations can be rewritten in matrix form:

\[
1_{1 \times G} \times C = -1_{1 \times N}, \tag{3.14}
\]

\[
1_{1 \times G} \times d = 0. \tag{3.15}
\]

Consequently, the generation redispatch problem under the affine response policy is mathematically expressed as:
Chapter 3. Comparison of Generation Dispatch Approaches

\[
\begin{align*}
\min_{\Delta \eta \in \mathcal{N}} \sum_{l=1}^{L} q_l(\Delta \eta, \Delta g) \\
\text{subject to} \\
\Delta g = C \times \Delta \eta + d \\
1_{1 \times G} \times C = -1_{1 \times N} \\
1_{1 \times G} \times d = 0 \\
\Delta g_{\min} \leq \Delta g \leq \Delta g_{\max}
\end{align*}
\]

where \(q_l(\Delta \eta, \Delta g)\) is a penalty function of line overloads (2.20); \(\mathcal{N}\) represents the domain of possible forecast errors; \(C\) and \(d\) are parameters of the affine response policy; and \(\Delta g_{\min}\) and \(\Delta g_{\max}\) represent the lower and upper bounds of active dispatchable generation on the system (2.21), (2.22).

The main innovation of this approach is that it allows controllable generators to respond to individual variations. For example, if a controllable generator is within the same (electrically-close) zone as a wind farm, it can be set to compensate for the local wind farm forecast errors. By contrast, the participation factor approach requires the generation dispatch to be based on the total imbalance, including both local and remote forecast errors.

### 3.3 Bilevel Programming Approach

Bilevel programming was first introduced in the field of game theory by a German economist, Heinrich von Stackelberg [33]. In his book, he described a strategic game that consists of a leader and a follower. Detailed elaboration of this hierarchical optimization problem is available in [34]. We use bilevel optimization to model the case where the controllable generation is optimally (i.e., with minimal transmission overloading) redispached.
3.3.1 An Overview of Bilevel Programming

The general formulation of a bilevel programming problem is as follows [35]:

\[
\min_{x \in \mathcal{X}, y} F(x, y) \quad (3.18)
\]

subject to

\[
\begin{aligned}
G(x, y) &\leq 0 \\
y &\in \arg \min_{\bar{y}} f(x, \bar{y}) \\
\text{subject to } g(x, \bar{y}) &\leq 0
\end{aligned}
\]  

(3.19)

where \(x \in \mathbb{R}^{n_1}, y \in \mathbb{R}^{n_2}\). The decision variables in this problem are divided into two classes, namely the upper-level (leader) variables \(x \in \mathbb{R}^{n_1}\), and the lower-level (follower) variables \(y \in \mathbb{R}^{n_2}\). Similarly, the two functions, \(F : \mathbb{R}^{n_1} \times \mathbb{R}^{n_1} \to \mathbb{R}\) and \(f : \mathbb{R}^{n_2} \times \mathbb{R}^{n_1} \to \mathbb{R}\) are referred to as the upper-level and lower-level objective functions, respectively. Another common names for these functions are the outer problem and the inner problem. The two vector-valued functions, \(G : \mathbb{R}^{n_1} \times \mathbb{R}^{n_1} \to \mathbb{R}^{m_1}\) and \(g : \mathbb{R}^{n_2} \times \mathbb{R}^{n_1} \to \mathbb{R}^{m_2}\) are called the upper-level constraints and lower-level constraints, respectively.

The two variables interact with each other, such that the upper-level variables \((x)\) make the first move, and then the lower-level variables \((y)\) react to optimally solve the lower-level problem with given upper-level variables. The upper-level problem \(F(x, y)\) contains a nested optimization task that corresponds to the lower-level optimization problem \(f(x, y)\), so that it can anticipate the optimal response of the lower-level variables before optimizing its own problem. This set of hierarchical optimization problem is asymmetric in nature, where the upper-level variables and the lower-level variables can not be interchanged.

3.3.2 Bilevel Programming Formulation

For bilevel programming, the problem discussed in this thesis can be reinterpreted as to find the maximum transmission line overloads due to the forecast errors despite optimal
generation redispatch of controllable generators. The mathematical representation of the problem is as follows:

\[
\begin{align*}
\max_{\Delta \eta \in \mathcal{N}} & \sum_{l=1}^{L} q_l(\Delta \eta, \Delta g) \\
\text{subject to} & \quad \Delta g \in \arg \min_{\Delta \tilde{g}} \sum_{l=1}^{L} q_l(\Delta \eta, \Delta \tilde{g}) \\
& \quad 1_{1 \times N} \times \Delta \eta + 1_{1 \times G} \times \Delta \tilde{g} = 0 \\
& \quad \Delta g_{\min} \leq \Delta \tilde{g} \leq \Delta g_{\max}
\end{align*}
\]

where \( q_l(\Delta \eta, \Delta g) \) is a penalty function of line overloads (2.20); \( \mathcal{N} \) represents the domain of possible forecast errors; and \( \Delta g_{\min} \) and \( \Delta g_{\max} \) represent the lower and upper bounds of active dispatchable generation on the system (2.22), (2.21).

By bilevel optimization terminology, (3.20) is the upper-level problem and (3.21) is the lower-level problem. In this optimization problem, the upper-level variable and lower-level variable are the net power injection forecast errors (\( \Delta \eta \)) and generation redispatch decision (\( \Delta g \)), respectively.

The hierarchical structure of BLP makes it difficult to solve. Several methods are elaborated in [34]. The convex, piecewise-linear characteristics of the penalty function (2.20) makes the Karush-Kuhn-Tucker (KKT) approach the most easy and direct method. The following section details replacing the lower-level problem with its KKT conditions and subsequently representing the entire BLP as a mixed-integer linear optimization problem.

### 3.3.3 Transfer Lower-level Optimization Problem into KKT Constraints

Due to the hierarchical structure of BLP, finding a solution could be very difficult. In practice, an appealing approach is to replace the lower-level optimization problem with
its KKT conditions, which include complementarity constraints [36]. Detailed assessment about this approach is included in [37].

Recall from former section, the lower-level problem of the BLP assuming fixed net power injection forecast errors ($\Delta \eta$) is:

$$\begin{align*}
\min_{\Delta g \in \mathbb{R}^G} & \sum_{l=1}^{L} q_l(\Delta \eta, \Delta g) \\
\text{subject to} & \begin{cases}
1_{1 \times N} \times \Delta \eta + 1_{1 \times G} \times \Delta g = 0 \\
\Delta g_{\min} \leq \Delta g \leq \Delta g_{\max}
\end{cases}.
\end{align*}$$

(3.22)

(3.23)

Denote the objective function as a variable $p$. First of all, we rewrite the piecewise objective function based on the discussion in Chapter 2:

$$\begin{align*}
-p & \preceq 0, \\
-\Phi \times p - \Psi_N \times \Delta \eta - \Psi_G \times \Delta g + \Delta f_{\min} & \preceq 0, \\
-\Phi \times p + \Psi_N \times \Delta \eta + \Psi_G \times \Delta g - \Delta f_{\max} & \preceq 0,
\end{align*}$$

(3.24)

(3.25)

(3.26)

where $\Phi \in \mathbb{R}^{L \times L}$ is the diagonal matrix of line ratings and $\Delta f_{\min}$ and $\Delta f_{\max}$ are the lower and upper bounds of change in line flows ((2.15) and (2.16)).

Hence, the lower-level optimization problem becomes:

$$\begin{align*}
\min_{\Delta g \in \mathbb{R}^G, p \in \mathbb{R}^L} & \sum_{l=1}^{L} p_l \\
\text{subject to} & \begin{cases}
1_{1 \times N} \times \Delta \eta + 1_{1 \times G} \times \Delta g = h_0 = 0 \\
-p = h_1 \preceq 0 \\
-\Phi \times p - \Psi_N \times \Delta \eta - \Psi_G \times \Delta g + \Delta f_{\min} = h_2 \preceq 0 \\
-\Phi \times p + \Psi_N \times \Delta \eta + \Psi_G \times \Delta g - \Delta f_{\max} = h_3 \preceq 0 \\
-\Delta g + \Delta g_{\min} = h_4 \preceq 0 \\
\Delta g - \Delta g_{\max} = h_5 \preceq 0
\end{cases},
\end{align*}$$

(3.27)

(3.28)
where \((h_0, h_1, h_2, h_3, h_4, h_5)\) denote the constraints of the lower-level optimization problem. The Lagrangian of the lower-level problem is:

\[
\mathcal{L}(\Delta g, p, \lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5) = 1^T p + \lambda_0 h_0 + \lambda_1^T h_1 + \lambda_2^T h_2 + \lambda_3^T h_3 + \lambda_4^T h_4 + \lambda_5^T h_5,
\]

(3.29)

where \((\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5)\) are Lagrange multipliers associated with constraints \((h_0, h_1, h_2, h_3, h_4, h_5)\).

Because it is a linear program, the global minimizer of the optimization problem should also be a local minimizer of the problem. Hence, one condition of optimality is that the stationarity conditions must be satisfied. These conditions are obtained by setting the gradient of the Lagrangian (3.29) with respect to \(\Delta g\) and \(p\) to zero:

\[
\nabla_{\Delta g} \mathcal{L}(\cdot) = \lambda_0 1_{1 \times G} - \lambda_2^T \Psi_G + \lambda_3^T \Psi_G - \lambda_4^T + \lambda_5^T = 0_{1 \times G},
\]

(3.30)

\[
\nabla_p \mathcal{L}(\cdot) = 1_{1 \times L} - \lambda_1^T - \lambda_2^T \Phi - \lambda_3^T \Phi = 0_{1 \times L}.
\]

(3.31)

In addition to the stationarity conditions, the constraints of the lower-level optimization problem must be enforced at the optimum (referred to as the primal feasibility constraints):

\[
1_{1 \times N} \times \Delta \eta + 1_{1 \times G} \times \Delta g = h_0 = 0,
\]

(3.32)

\[
-p = h_1 \preceq 0,
\]

(3.33)

\[
-\Phi \times p - \Psi_N \times \Delta \eta - \Psi_G \times \Delta g + \Delta f_{\min} = h_2 \preceq 0,
\]

(3.34)

\[
-\Phi \times p + \Psi_N \times \Delta \eta + \Psi_G \times \Delta g - \Delta f_{\max} = h_3 \preceq 0,
\]

(3.35)

\[
-\Delta g + \Delta g_{\min} = h_4 \preceq 0,
\]

(3.36)

\[
\Delta g - \Delta g_{\max} = h_5 \preceq 0.
\]

(3.37)

At the optimum, complementary slackness conditions must also be satisfied. These are represented using complementarity constraints relating the Lagrange multipliers and
the “slack” in the corresponding inequalities:

\[ \lambda_1^T \times h_1 = 0, \quad (3.38) \]
\[ \lambda_2^T \times h_2 = 0, \quad (3.39) \]
\[ \lambda_3^T \times h_3 = 0, \quad (3.40) \]
\[ \lambda_4^T \times h_4 = 0, \quad (3.41) \]
\[ \lambda_5^T \times h_5 = 0. \quad (3.42) \]

For a given inequality constraint \( h_i \), either the constraint itself is equal to zero, or
the associated Lagrange multiplier (\( \lambda_i \)) is equal to zero. If \( h_i \) is equal to zero, then this
constraint is active (binding) and restricts the possible changes of the variables. If \( \lambda_i \)
is equal to zero, then the constraint is inactive (non-binding) and doesn’t restrict the
possible changes of the variables.

The final component of the KKT conditions is that the Lagrange multipliers should
never be less than zero (the dual feasibility constraints):}

\[
\begin{bmatrix}
\lambda_1 \\
\lambda_2 \\
\lambda_3 \\
\lambda_4 \\
\lambda_5 \\
\end{bmatrix} \succeq 0. \quad (3.43)
\]

Hence, (3.30)-(3.32) and (3.38)-(3.43) together can replace the original lower-level
optimization problem (3.21). The BLP is transferred into a single-level mixed-integer
linear programming (MILP) problem.

In our implementation, this was accomplished by using the built-in KKT constraint
builder in YALMIP [38] and adding the lower-level optimization problem as a set of
constraints to the upper-level problem.
The BLP optimization problem discussed in this thesis can be solved by any solver in the market that demonstrates good performance solving MILP problems.
Chapter 4

Case Study

4.1 Experimental Methodology

The solutions for each generator redispatch policy were programmed in MATLAB. The experimental results were obtained using Gurobi v5.1.1 [39] as the linear programming (the participation factor and the affine response approaches) and mixed-integer linear programming (the bilevel programming approach) solver. MATPOWER v4.0 [40] was used to calculate the ISF matrix ($\Psi$ in (2.5)) and the base case DCOPF ($f_{\text{base}}$). The computer used to run the experiments has an Intel Xeon CPU E5-1620 (3.60 GHz) and 8 GB of RAM. All experimental results in this thesis were generated based on 10 repeated simulations. Although the proposed problem formulation can incorporate both load and variable generation forecast errors, the case studies consider only wind forecast errors for simplicity.

The Overbye 37-bus system and IEEE 118-bus system used for simulation contained conventional generators only. Therefore, wind farms were added to the systems based on the following criteria:

First of all, the sensitivity to the power injection of existing generators of each line was evaluated as the sum of the absolute values of the ISFs associated with all existing
dispatchable generators. For each line \( l \), the sensitivity was calculated as:

\[
SISF_l = \sum_{i=1}^{G} |\Psi_{G_{(l,i)}}|,
\]

where \( \Psi_{G_{(l,i)}} \) is the ISF of line \( l \) to the controllable dispatchable generators at bus \( i \). A small \( SISF \) value indicates that existing dispatchable generators possess less control over flows on the line.

The \( SISF \)s were then sorted in ascending order. Starting from line \( l \) with the smallest \( SISF \), a wind farm was placed at bus \( i \) that had the largest absolute value of ISF over line \( l \), thus maximizing the effect of wind generation (or wind generation forecast error) on flow at line \( l \). The process was repeated on the line with the second smallest \( SISF \), the line with the third smallest \( SISF \), and so forth, until a desired number of wind farms were added to the system.

Wind farm sites chosen above contain the largest potential impact on the transmission lines, since these locations have the largest influence on the most vulnerable lines.

Forecast power output for every wind farm is 10 MW, for simplicity.

4.2 Case I: 37-bus System

The first test system is a 37-bus system from the Glover, Sarma, and Overbye power system analysis textbook [2]. It consists of eight conventional generators and 54 branches, as illustrated in Fig. 4.1. In order to analyze the impact on line loading, the system is modified by increasing the loads, controllable generator outputs and generation limits by 90%, while leaving the transmission network unchanged. The ramp rates (up and down) of the conventional generators are assumed to be 30% of plant ratings, which lies within the range of ramp rates of intermediate and peaking units. Eight wind farms are added to the system, at buses 1, 3, 6, 10, 11, 12, 25 and 36—based on the selection criteria discussed in the previous section.
To evaluate the performance of the three dispatch policies, 9 different bounds (i.e., $N$ in Chapter 3) are tested to represent the forecast error at each wind farm: $\pm 0$ MW, $\pm 5$ MW, $\pm 10$ MW, $\pm 15$ MW, $\pm 20$ MW, $\pm 25$ MW, $\pm 30$ MW, $\pm 35$ MW and $\pm 40$ MW, with an equal interval of 5 MW.

The performance is evaluated based on two parameters, i.e., objective value and computational time. The results are illustrated in Fig. 4.2 and Fig. 4.3.

The objective value is illustrated in Fig. 4.2. An upward trend is observed on all three curves. The objective values for forecast error bounds up to $\pm 15$ MW are zero on all three curves, which indicate that it is feasible to maintain power balance without any violation of the existing line flow constraints using any of the three dispatch policies.
When bound for forecast errors is ±20 MW, the objective value obtained using the participation factor policy increases dramatically to 0.066 p.u., whereas those using the affine response and the bilevel programming policies are both 0.001 p.u. (from Table A.1). Non-zero objective values indicate that some overloads will occur in order to maintain power balance. Another finding is that under the same forecast error bound scenario, the objective value obtained using the participation factor policy is always higher than that of the affine response policy and that the objective value obtained using the affine response policy is always higher than that of the bilevel programming policy. This observation complies with our expectation. The affine response approach is mathematically a generalized version of the participation factor approach; hence it may find better dispatch solution than the participation factor approach. The bilevel programming approach doesn’t imply linear relation between $\Delta \eta$ and $\Delta g$. Therefore, it may find optimal dispatch solution when compared with the other two approaches. As forecast error bound on wind generation expands, the differences in overloads among the three policies become more and more evident as well.
Figure 4.2: Comparison of objective value among three different generation redispatch policies (37-bus system)
The average computational time is illustrated in Fig. 4.3. It is observed that for the same level of wind forecast errors, the computational times of the participation factor policy and the affine response policy are very similar and the time difference is negligible. There is very limited increase in computational time when forecast error zone enlarges for both the participation factor and the affine response policies. Neither of them runs beyond 0.1 second (from Table A.2). In contrast, the computational time of the bilevel programming policy increases dramatically as forecast error range expands. It takes much more time to solve the problem by bilevel programming (in comparison to the other two methods). For instance, it takes 2.445 seconds to solve with bilevel programming policy at forecast error bound of ±40 MW, whereas computational times for the participation factor policy and the affine response policy are 0.043 second and 0.073 second respectively. This difference results from the hierarchical structure of bilevel programming.
Figure 4.3: Comparison of computational time among three different generation redispatch policies (37-bus system)
4.3 Case II: IEEE 118-bus System

The second case study is based on the IEEE 118-bus system, a mid-sized system that is often used in power system literature. This system consists of 54 dispatchable generators and 186 branches, as illustrated in Fig. 4.4 [3]. Data for the transmission line ratings is taken from [41]. Eight wind farms are introduced to the system—at buses 1, 2, 3, 52, 53, 55, 114, and 115—based on the same selection criteria as used for the 37-bus system.

Altogether 33 sets of forecast error scenarios from $\pm 0$ MW to $\pm 160$ MW (at each wind farm bus), with an equal interval of 5 MW, are tested for each dispatch policy. The results are illustrated in Fig. 4.5, Fig. 4.6 and Fig. 4.7.

The objective value is illustrated in Fig. 4.5. There is an escalating trend for all of
the approaches. All three policies present solutions with zero objective values for forecast errors up to ±90 MW, meaning that the dispatch solutions satisfy both power balance constraints and line flow constraints within these forecast error levels. When forecast error bound is ±95 MW, generation redispatch with the participation factor policy fails with an overflow of 0.058 p.u. (from Table A.3). As forecast error bound expands, the overflow increases dramatically. Generation redispatch with the affine response policy and the bilevel programming policy successfully maintain zero overflow for forecast error bounds of ±95 MW, ±100 MW, ±105 MW and ±110 MW. At ±115 MW forecast error, an objective value of 0.011 p.u. for both the affine response policy and the bilevel programming policy indicates the emergence of overflow. The objective values for the affine
response and the bilevel programming policies both increase as forecast error bound enlarges and they remain identical under same wind forecast error scenario. Distinctions emerge at the ±140 MW forecast error range. From the ±140 MW forecast error bound, the bilevel programming policy gives redispacht solutions with a lower degree of transmission overloads, when compared with the affine response policy. Again the objective value obtained using the participation factor policy is always higher than that of the affine response policy; the objective value obtained using the affine response policy is always higher than that of the bilevel programming policy; the differences among the three policies increase as the forecast error bound expands. In this test system, the affine response and bilevel programming objective values are very close. One explanation is that dispatchable generators are distributed throughout the network. Therefore, the affine response approach can effectively direct dispatchable generators to compensate nearby wind variation.

A comparison of average computational time among all three policies is illustrated in Fig. 4.6 and the comparison between the participation factor and the affine response policies is illustrated in Fig. 4.7. From Fig. 4.6, it is observed that the difference among three policies is rather small for wind forecast error bounds up to ±105 MW. For wind forecast error bounds beyond ±105 MW, the computational time of bilevel programming policy increases much more dramatically than the participation factor and the affine response policies. At the ±130 MW forecast error bound, the computational time for the bilevel programming policy arrives at a local peak, which demonstrates the randomness in the branch-and-bound process presented by Gurobi to solve bilevel programming. It also takes far more time to solve for the bilevel programming policy than the participation factor and the affine response policies—at the highest forecast error levels, the computational tractability of this approach is questionable (particularly if it were applied to a 3000-bus system, such as the Ontario transmission system model).
Figure 4.6: Comparison of computational time among three different generation redispatch policies (IEEE 118-bus system)
If we compare the computational time of the participation factor and the affine response policies, as illustrated in Fig. 4.7, we can find out that the computational time of affine response policy is generally higher than that of participation factor policy and that computational time of the affine response policy increases more dramatically in comparison to the participation factor policy. This can be explained with a close scrutiny of the decision variables associated with the policies. The decision variables for the participation factor policy are $\beta$ and $\gamma$ as defined in (3.4) and those for the affine response policy are $C$ and $d$ as defined in (3.11). The sizes of $C$ and $d$ are much larger than those of $C$ and $d$, in comparison to the 37-bus System case. We can make an educated guess that the difference in computation time for the affine response and the participation factor policies will be more noticeable if applied to larger systems with more wind penetration.
Figure 4.7: Comparison of computational time between the participation factor and the affine response policies (IEEE 118-bus system)
4.4 Application to Transmission Upgrades

In addition to the real-time operations application, the algorithms can also perform a key role in transmission upgrades. Variable generation integration has increased potential need for adequate transmission expansion [42]. As demonstrated by the case studies, line overloads are unavoidable when there are large forecast errors in wind generation. Transmission upgrades could be used to ensure that the introduction of variable generation does not result in forced outage of lines, load shedding, or curtailment of variable generation. Intuitively, it is more cost-effective to upgrade fewer transmission lines with higher value rather than performing minor upgrades to a large number of lines. The procedure we followed for transmission upgrades is shown in Fig. 4.8.

First of all, the previously defined optimization problem is solved with the affine response or the bilevel programming dispatch policies. If the objective value of the optimization problem is zero, it is not necessary to perform any transmission upgrades. As discussed in the former section, non-zero objective value on the IEEE 118-bus system emerges when forecast error bound is $\pm 115$ MW. Therefore, an exhaustive research on all possible transmission upgrades solutions that satisfy line flow constraints with one single new transmission line is performed, starting from wind deviations of $\pm 115$ MW. From the pool of possible single-line transmission upgrades solutions, the one with minimum investment cost (i.e., minimum capacity increase, as a percentage of the initial line rating) is selected. If there is no feasible solution for a single-line upgrade, an exhaustive search over all two-line upgrade is performed. From the pool of possible double-line transmission upgrades solutions, the one with minimum investment cost—an upgrade of two lines—is selected. If there is no double-line solution available, we move on to triple-line transmission upgrades (and so on).

Table 4.1 presents the results of performing the exhaustive research on transmission upgrades with the affine response policy on the IEEE 118-bus system.

For forecast error bounds up to $\pm 130$ MW, the transmission upgrades problem can
be solved with one additional transmission line. When the forecast error bound is ±135 MW, two extra lines are needed so that overloading on the system is eliminated.

Table 4.2 presents the results of performing the exhaustive research on transmission upgrades with the bilevel programming policy on the IEEE 118-bus system. For forecast
error bounds up to ±130 MW, the system can handle the forecast errors with a single-line upgrade. When the forecast error bound is ±135 MW, a double-line upgrade is needed to ensure that overloads do not occur. When the forecast error bound reaches ±150 MW, a triple-line upgrade is needed to ensure that no overload occurs. It is observed that the upgrade solutions are the same as those obtained with the affine response policy for the forecast errors ranges up to ±135 MW.

The results indicate that the proposed algorithms are able to find a small (in all cases tested, minimal) set of transmission line upgrades to accommodate a given set of forecast errors. This is expected, since it is well-known that utilization of the 1-norm in an objective function will tend to provide sparse solutions. For example, the Lagrangian
form of least-squares (sparse) $l_1$-regulation is [43]:

$$\hat{\beta}_{\text{lasso}} = \arg\min_{\beta} \frac{1}{2} \sum_{i=1}^{N} (y_i - \beta_o - \sum_{j=1}^{P} x_{ij} \beta_i)^2 + \lambda \sum_{j=1}^{P} |\beta_i|. \quad (4.2)$$
Chapter 5

Conclusion and Future Work

5.1 Conclusion

In this thesis, three policies are presented for generation redispatch in response to wind generation forecast errors, with the goal of minimizing the transmission overloads. The generation redispatch policies are tested on two different systems and the result is summarized in Table 5.1.

<table>
<thead>
<tr>
<th>Policy category</th>
<th>Dispatch solution</th>
<th>Computational time</th>
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<tr>
<td>Participation factor policy</td>
<td>Worst</td>
<td>Shortest</td>
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<tr>
<td>Affine response policy</td>
<td>Moderate</td>
<td>Moderate</td>
</tr>
<tr>
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<td>Best</td>
<td>Longest</td>
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</table>

The participation factor policy and the affine response policy perform well in terms of computational time, whereas the bilevel programming policy generates better generation redispatch solutions (i.e., dispatch that reduces transmission line loading in comparison to the other two policies).

There is always a trade-off between better redispatch solutions and less computational time. Different dispatch policies should be chosen based on factors such as system size,
dispatchable generator distribution pattern and variable generation distribution pattern. For large systems where dispatchable generators are distributed throughout the network, the affine response approach is able to find solutions nearly as good as the bilevel programming approach. However, with increasing system size, it also takes more time to solve than the participation factor approach.

The ideal case is that feasible decisions which satisfy both power balance constraints and line flow constraints are made within limited calculation time. If it is not feasible to satisfy both constraints, the decision that satisfies power balance constraints and minimizes line overflow is selected. The following generation redispatch procedure is proposed in this thesis, as illustrated in Fig. 5.1.

First of all, the participation factor policy is used for the dispatch. If overloads occur with the participation factor policy, we switch to the affine response policy. If affine response policy is not able to eliminate the overloads, the bilevel programming policy is used. This procedure provides minimal calculation time required to accommodate the net power injection forecast errors.

In conclusion, the affine response policy offers good tradeoff between computational time and dispatch performance for large systems where dispatchable generators are distributed throughout the network. Bilevel programming is impractical for large systems with significant forecast errors, as indicated in the IEEE 118-bus system.

Exploration on transmission upgrades indicates that use of l-norm gives sparse overloading that may be applicable for planning.
Figure 5.1: Flowchart of the proposed generation redispatch procedure
5.2 Future Work

The proposed research has shown that the variability in load and variable generation can be readily incorporated into an optimization framework by using robust optimization approaches (i.e., the participation factor approach and the affine response approach) or the bilevel programming approach.

The results have shown that optimal dispatch of generation resources (e.g., as performed in some transmission planning and production costing software) could potentially be replaced by an affine response approach, which has the potential to significantly reduce the computational time of these analyses. For example, the affine response could be incorporated in automatic generation control.

Another application of this work could be to provide a tool set for evaluating the relative trade-offs of transmission upgrades vs. the introduction of additional controllable resources (e.g., new generators or storage), both of which are routinely considered in the context of long-term energy planning in Ontario.

In the thesis, the line flows are calculated using dc power flow, which provides a good approximation in a short time frame. In future studies, we could upgrade accuracy by utilizing a linearized ac power flow model to calculate the initial power flow and the power flows resulted from forecast errors. This would not only give more precise results but also allow for analysis of other quantities of interest (e.g., voltage levels).

Lastly, the three optimization algorithms discussed in this thesis could be incorporated in demand response (DR). Demand response, which enables electricity consumers to adjust their electricity usage in response to price signals and system needs, has been embraced by Ontario’s electricity market. Demand response resources not only help improve energy adequacy in the market, they also enhance power system reliability. Over the past few years, the IESO has expanded the role of demand response within Ontario’s electricity market. One effective demand response program is the annual Demand Response Auction, which invited DR suppliers (i.e., large consumers, such as dispatchable
loads, as well as aggregators of small institutional, commercial and industrial customers) to compete to provide DR capacity [44]. The first DR Auction was held in December 2015, and invited offers for summer and winter commitment periods. The IESO’s Demand Response Pilot Projects has so far secured up to 80 MW of DR representing 20 projects which are required to vary their consumption in response to IESO dispatch instructions for at least 100 hours per contract year [45]. The participation factor algorithm, the affine response algorithm and the bilevel programming algorithm could be utilized in determining the consumption of dispatchable loads of Demand Response programs.
Bibliography


Appendix A

Datasheet

Table A.1: Comparison of Objective Value among Three Different Generation Redispatch Policies (37-bus System)

<table>
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<tr>
<th>Forecast error (± MW)</th>
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Table A.2: Comparison of Computational Time among Three Different Generation Redispatch Policies (37-bus System)

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Table A.3: Comparison of Objective Value among Three Different Generation Redispacht Policies (IEEE 118-bus System)

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Table A.4: Comparison of Computational Time among Three Different Generation Redispacht Policies (IEEE 118-bus System)

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