New ancillary service market design to improve MW-frequency performance: reserve adequacy and resource flexibility

Guangyuan Zhang
Iowa State University

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New ancillary service market design to improve MW-frequency performance: Reserve adequacy and resource flexibility

by

Guangyuan Zhang

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Electrical Engineering

Program of Study Committee:
James D McCalley, Major Professor
Ian Dobson
Venkataramana Ajjarapu
Leigh Tesfatsion
William Gallus

Iowa State University
Ames, Iowa
2015
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<td>PFC</td>
<td>Primary Frequency Control</td>
</tr>
<tr>
<td>SFC</td>
<td>Secondary Frequency Control</td>
</tr>
<tr>
<td>TFC</td>
<td>Tertiary Frequency Control</td>
</tr>
<tr>
<td>AGC</td>
<td>Automatic Generation Control</td>
</tr>
<tr>
<td>UC</td>
<td>Unit Commitment</td>
</tr>
<tr>
<td>ED</td>
<td>Economic Dispatch</td>
</tr>
<tr>
<td>PFR</td>
<td>Primary Frequency Reserve</td>
</tr>
<tr>
<td>SFR</td>
<td>Secondary Frequency Reserve</td>
</tr>
<tr>
<td>FRP</td>
<td>Flexible Ramping Product</td>
</tr>
<tr>
<td>LFC</td>
<td>Load Frequency Control</td>
</tr>
<tr>
<td>BAAL</td>
<td>Balancing Authority ACE Limits</td>
</tr>
<tr>
<td>DCS</td>
<td>Disturbance Control Standard</td>
</tr>
<tr>
<td>DR</td>
<td>Demand Response</td>
</tr>
<tr>
<td>LF</td>
<td>Load Following</td>
</tr>
<tr>
<td>GR</td>
<td>Governor Response</td>
</tr>
<tr>
<td>UFLS</td>
<td>Under-Frequency Load Shedding</td>
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<tr>
<td>ACE</td>
<td>Area Control Error</td>
</tr>
<tr>
<td>CPS</td>
<td>Control Performance Standard</td>
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<tr>
<td>MLR</td>
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ACKNOWLEDGEMENTS

I will never be able to finish this dissertation without the guidance and help from my advisor, my committee members, my family and my friends.

Firstly, I would like to express my deepest gratitude to my advisor, Dr. James McCalley for his guidance and patience during my PhD period. His research insight and dedication always encourage me to explore further in my research area. With his guidance and advisory, I become more confident in tackling the next research challenge.

I would also like to express my thankfulness to my committee members: Dr. Venkataramana Ajjarapu, Dr. Leigh Tesfatsion, Dr. Ian Dobson and Dr. William Gallus for guiding my research during the past several years and helping me to develop my background and knowledge in my research area.

I would also thank all my colleagues and friends during my time in Ames. I will never forget the moments that I discuss the tough research questions with my friends and how helpful their suggestions are for my research path.

I would also express my wholehearted gratitude for my parents, Jiajun Zhang and Hua Zhou. It is them encouraging me to pursue my PhD degree and keep persevering in its pursuit. I apologize for not being able to accompany them during past years.

Finally, I want to express my special thanks to my girlfriend, Xian Guo, for her patience and love at the toughest moment during my PhD time period.
ABSTRACT

With the high penetration of renewable energy resources such as wind and solar, the power system is facing the degradation of frequency response. The major reasons for the degradation of frequency performance can be summarized as following reasons: first, the cheap and clean renewable energy is displacing the conventional thermal generator. While the wind turbine is connecting with the bulk power grid with AC-DC-AC converter and the solar panel is connected to the grid via the DC-AC inverter. The power electronic device isolates the wind or solar unit from the synchronous bulk power grid, therefore, the wind and solar is not designed to response the frequency excursion naturally. Secondly, the wind and solar energy is highly dependent on the weather condition therefore is highly uncertain and variable. This uncertainty and variability increase the difficulties for balancing the generation and demand therefore causes the frequency performance deteriorate than before.

In this dissertation, the major contribution is to design the more efficient and effective frequency responsive reserve methods to ensure the reserve adequacy and resource flexibility in handling deteriorating frequency performance. The frequency constrained economic dispatch is first proposed to incorporate the frequency dynamic constraint into economic dispatch problem to ensure sufficient primary and secondary frequency reserve. Then the model is extended to a stochastic unit commitment model with inertial, primary and secondary frequency constraints and the demand side frequency responsive reserve. The method for regulation reserve requirement is also proposed to meet the satisfactory frequency performance under normal operation condition. The Multiple Linear Regression model is
applied to determine the real time regulation requirement for satisfying the target CPS1 metric. For the slower time scale, the high penetration of renewable energy can cause the insufficient flexible ramping capability. In this dissertation, the stochastic look-ahead economic dispatch model with deliverable flexible ramping product is presented to provide the sufficient ramping capability so that the frequency performance is improved and real time price spike is reduced.
CHAPTER 1 INTRODUCTION

1.1 Overview

The objective of the power system MW-frequency control is to keep the generation as close as possible to the demand so that the frequency deviation maintained within a close bandwidth around the nominal value (60 HZ in US). This objective is achieved by several time scale coupled control ranging from a few seconds to a few minutes which includes: Inertial Response (IR), Primary Frequency Control (PFC)/Governor Response (GR), Secondary Frequency Control (SFC)/Automatic Generation Control (AGC) and Tertiary Frequency Control (TFC)/Load Following (LF). The time scale separation of the frequency response process is illustrated in Fig 1.1 [1]; the IR occurs right after the contingency event such as loss of generation and lasts for only a few seconds. IR compensated for supply and demand imbalance by releasing the energy from rotating mass and it results in the reduction of rotor speed. The PFC follows right after the IR and lasts from 20 seconds to 1 minute. The PFC adjusts the governor valve to arrest the frequency dip and stabilize the frequency to steady state. In the contingency situation, the SFC responds after the PFC and recovers the frequency back to the nominal value. In the normal operation condition, the SFC or AGC is run every 2 to 6 seconds to maintain the frequency as close as possible to nominal and tie-line flow close to the schedule [2]. This is done by the centralized control center by sending the raise/lower signal to each participating units which are selected by Economic Dispatch (ED) and Unit Commitment (UC), based on their bid-in cost price. ED is run every 5 minutes and may look ahead several intervals. The TFC or load following is the capability of the
generation unit to respond the economic dispatch signal subjects to its ramp rate limitation. During the TFC process, the operator recovers the deployed PFC and SFC reserve from the spinning capacity or off-line capacity in preparing for the next contingency event. Economic Dispatch co-optimizes the energy and reserve by using the Linear Programming (LP) technique. The Unit Commitment is implemented to determine the unit ON/OFF status and schedule the energy and reserve by using a Mixed Integer Linear Program (MILP).

![Time Scale Separation of Frequency Response](image)

Fig 1.1 Time Scale Separation of Frequency Response

The frequency response reserve is aimed to maintain frequency within a narrow band around 60 Hz. Frequent failure to maintain frequency within the band results in financial penalties motivated by the desire to avoid activation of under frequency load shedding (UFLS), undesired generator tripping, and in the worst case, damage to turbine-generator sets. So the sufficiency of the frequency response reserve plays a critical role in maintaining the power system reliability.

The frequency responsive reserve procurement is implemented in the ED or UC based on some static approach. For example, the Primary Frequency Reserve (PFR) requirement should be greater than the most severe single contingency; the Secondary Frequency Reserve
(SFR) or regulation reserve requirement is 1% of the peak load or based on other static approach as illustrated in Table 1.1.

Table 1.1 Regulation Reserve Requirement from various Balancing Authorities

<table>
<thead>
<tr>
<th>Region</th>
<th>Regulation Requirement</th>
</tr>
</thead>
<tbody>
<tr>
<td>PJM</td>
<td>1% of peak load during peak hour and 1% of valley load during off-peak hour</td>
</tr>
<tr>
<td>NYISO</td>
<td>Based on hour of day, weekday/weekend and season</td>
</tr>
<tr>
<td>ERCOT</td>
<td>Based on 98.8th percentile of regulation reserve utilized in previous 30 days and same month of previous year and adjusted by installed wind penetration</td>
</tr>
<tr>
<td>CAISO</td>
<td>CAISO sets its Regulation reserve target as a percentage of CAISO Forecast of CAISO Demand for the hour</td>
</tr>
<tr>
<td>ISO-NE</td>
<td>Based on hour of day, weekday/weekend and month</td>
</tr>
<tr>
<td>MISO</td>
<td>MISO requirement is a bidirectional value varying between 300 MW to 500 MW depending on load level and time of the day</td>
</tr>
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</table>

These reserve requirements are included in the ED or UC as the reserve requirement constraints and they are deployed in the real time operation when needed. The static reserve requirement worked well in the past since the load was less variable and less uncertain. But with large penetration of intermittent resource in the future, the traditional reserve requirement approach may not be reliable and sufficient due to the increasing variability and uncertainty from the intermittent resources. Under this background, there is much interest to find an alternative approach to procure frequency responsive reserve. In this dissertation, we will propose more economic and effective methods to determine the frequency responsive reserve requirement from different time scale processes, including IR, PFR, SFR and TFR. The numerical results proposed in the each subsequent chapter will illustrate the higher economic efficiency and better frequency performance by using the proposed methods. The
subsequent four chapters will present different models for procuring the sufficient frequency responsive reserve including:

1) The procurement of PFR and SFR in the contingency condition by integrating the frequency dynamics equations into the ED to prevent the Under Frequency Load Shedding (UFLS) and prolong frequency restoring time.

2) The procurement of IR, PFR and SFR in Stochastic Unit Commitment (SUC) by combining the dynamics of load frequency control (LFC) and stochastic generation outage and net load uncertainty into the UC model.

3) The procurement of regulation reserve under normal operation condition based on the target CPS1 metric and Multiple Linear Regression (MLR) model.

4) The procurement of flexible ramping product (FRP) in look-ahead stochastic ED problem to handle the increasing net load variability and uncertainty.

Since different markets have different naming conventions, in order to avoid confusion, we assume that the PFR and governor response, SFR and regulation reserve, load following and FRP are interchangeable.

1.2 Literature Review

There are several literatures proposed to include PFR related constraints into the UC or ED model. In [3], the ED problem is formulated as a two stage stochastic program in which the post-contingency minimum frequency constraints are formulated using the simplified frequency dynamic model. In [4], the governor ramp rate constraints is included into the ED problem to prevent the UFLS. In [5] and [6], the new market design for the PFR product is
proposed. In [7], the piecewise linear technique is employed to linearize the non-linear minimum frequency deviation and include it into the UC problem. In [8], a multi-period UC problem accounts for PFR constraints is formulated and solved. Above literatures are mostly focused on the PFR adequacy under contingency.

There are also numerous literatures focusing on the regulation reserve or SFR requirement. In [9], the standard deviation of the net load variation is used to determine the regulation reserve requirement, and the confidence interval is adjusted to reflect the different risk preference. In [10]-[11], researchers at the National Renewable Energy Laboratory (NREL) proposed a method to determine regulation reserve requirement based on the variance of wind forecast error and load forecast level. Pacific Northwest National Laboratory (PNNL) proposed a method to estimate the regulation reserve requirement based on Balancing Authority ACE Limits (BAAL) in which the regulation reserve requirement is calculated as the adequate capacity to bring the ACE back to BAAL limit [12]. Chávez et al. analyzed the Electric Reliability Council of Texas (ERCOT) regulation reserve adequacy by a simplified dynamic model [13] and proposed a dynamic method in determining the optimal AGC gain to meet the single Balancing Authority (BA) CPS1 criteria [14]. Makarov et al. assessed the impact of wind integration on regulation and load following requirement for California Independent System Operator (CAISO) and presented a statistical approach to evaluate the regulation capacity, ramp rate and ramp duration requirement [15]. The regulation reserve requirement for various BA is also summarized in Table 1.1, and most of them are based on rule of thumb [16].
In the slower time scale process, people observed that the traditional regulation reserve (AGC control) is not sufficient to handle the net load fluctuation under high renewable penetration. For instance, California ISO expected that with 50% solar penetration, they will encounter four ramp periods in the future. The first ramp of 8,000 MW in upward direction occurs in the morning starting around 4:00 a.m. as people get up and set out to work. The second, in the downward direction, occurs after the sun rises around 7:00 a.m. when on-line conventional generation is replaced by supply from solar generation resources. The minimum net-load in this period will be expected to be about 4,000 MW lower than current time and it may cause the significant over-generation risk. As the sun starts to set at around 4:00 p.m., the ISO must dispatch resources that can meet the third and most significant upward ramp. Immediately following this steep 11,000 MW ramp up, as demand on the system deceases into the evening hours, the ISO must reduce or shut down that generation to meet the last downward ramp [17]. Under this background and prediction, California ISO has proposed the flexible ramping product (FRP) to handle the intra-hour load following insufficiency. Some research has already been done both in industry and academia in this area. In Midcontinent ISO, the flexible ramping product is designed to cover the net load uncertainty in next 10 minutes [18]-[19]. In California ISO, the flexible ramping product is designed to provide load following flexibility for next 5 minute and may look ahead several intervals [20]-[21]. In [22], an optimization based model is used to evaluate the ramping capability requirement considering both the reliability and economics. In [23], a deterministic ramping capability model with transmission constraint is proposed to ensure its deliverability. In [24], both the deterministic and stochastic model is evaluated in designing the market for flexible ramping
product. In [25], a robust economic dispatch model is developed with ramping capability requirement and compared with the deterministic model.

1.3 Contributions

The overall contribution of this dissertation is to determine the frequency responsive reserve requirement in a more efficient and effective method so that the MW-frequency performance is improved under future high intermittent resource scenario. The specific contributions of this dissertation are summarized in Table 1.2 which includes the following four bullets:

1) Integrate ED model with PFR and SFR dynamics to prevent the Under Frequency Load Shedding (UFLS) and prolong frequency restoration time in contingency condition.

2) Integrate UC with IR, PFR and SFR dynamics and consider the stochastic feature of unit outage and wind ramping. And the frequency responsive demand response (DR) is modelled to provide the reserve when the conventional thermal units are insufficient.

3) Abstract the relationship between CPS1 and regulation reserve requirement via the Multiple Linear Regression (MLR) Method and determine the future regulation reserve requirement based on the MLR and desired CPS1 target.

4) A Stochastic ED model with deliverable FRP is developed to preserve the sufficient flexible ramping capability in handling the intra-hour net load variability and uncertainty.
Table 1.2 Summarization of dissertation contribution and literature review

<table>
<thead>
<tr>
<th>Overall Objective</th>
<th>Improve the MW-frequency control performance under high intermittent resource penetration</th>
</tr>
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<tbody>
<tr>
<td>Research direction</td>
<td>Direction A</td>
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<tr>
<td>Objective</td>
<td>Provide the sufficient contingency reserve to prevent the UFLS and meet the Disturbance Control Standard (DCS) requirement</td>
</tr>
<tr>
<td>New Method contributed by this dissertation</td>
<td>Integrate IR, PFR and SFR dynamic into ED and UC</td>
</tr>
<tr>
<td>List of Existing methods from literature review</td>
<td>1, ED with governor response ramp constraint [4], NREL propose the regulation reserve requirement based on wind forecast error and load level [11]</td>
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1.4 Outline of dissertation

Chapter 1 presents the background of this dissertation, the literature review in the related area, the contribution of the work and the outline of the dissertation.

Chapter 2 presents an integrated ED model including IR, PFR and SFR constraints. The purpose of IR constraint is to prevent the severe Rate-of-Change-of-Frequency (RoCoF). The purpose of the PFR constraint is to prevent the trigger for UFLS and arrest the frequency
deviation within a tolerable time. The purpose of the SFR constraint is to return the frequency back to nominal within a time limitation.

Chapter 3 presents a stochastic UC model which combines the IR, PFR and SFR dynamics with UC static constraints. The model procures sufficient IR, PFR and SFR to meet certain frequency performances. The stochastic programming technique and L-shape method are leveraged to model the multiple scenario combinations between wind output uncertainty and thermal unit outage. The frequency dynamics are simulated in Matlab/Simulink to compare the performance between traditional UC solution and proposed model solution.

Chapter 4 proposes a new method to determine the real time regulation reserve requirement based on the desired CPS1 target. The Multiple Linear Regression (MLR) model is developed to build the relationship between CPS1 and regulation reserve requirement as well as other load and wind condition. The stepwise method with cross validation (CV) is then used to select the most relevant features and reduce model complexity. The Recursive Least Square (RLS) method is used to calculate and update the model parameters in a real time environment. The case study shows the more stable and less volatile CPS1 trajectory and even lower procurement cost comparing to NREL method and PJM practice.

Chapter 5 proposes a stochastic ED with the FRP. The chapter starts with a model only includes system-wise FRP requirement, then introduce the model with the zonal FRP requirement. Lastly but most importantly, a two stage stochastic model with the nodal-level FRP is designed to handle the spatial-temporal net load uncertainty and variability. The solution is robust towards the most extreme scenarios which are represented as the vertices of
the uncertainty set. The network constraints are modelled to ensure the deliverability of the FRP.

Chapter 6 summarizes the dissertation and proposes the future work.
CHAPTER 2 MARKET OPERATION MODEL WITH PRIMARY AND SECONDARY FREQUENCY CONSTRAINTS

2.1 Introduction

A large load connection or a sudden loss of generation results in imbalance between generation and load and subsequent frequency deviation. Such frequency deviation is arrested by inertial response (IR) and then returned to a steady-state via Primary Frequency Response (PFR). The error between the resulting steady-state and the nominal frequency is corrected by the actions of the Secondary Frequency Response (SFR). Generation is then rebalanced to secure and economic set point and the reserve margin is restored via Tertiary Frequency Response (TFR).

The procurement of the needed three types of frequency response is determined by an ex-ante reserve market, making it necessary to account for sufficiency of resources to supply the needed frequency-related services in the market dispatch model. High penetration of wind and solar will impose increased requirement on SFR. Any resulting SFR shortage may then adversely affect PFR sufficiency, resulting in unsatisfactory frequency performance. A number of research works have already been published on incorporating frequency constraints into a market dispatch model, including those which do so within an ED model [3], [4] and [26] and those which do so within a UC model [8]. References [5] and [6] also propose new market design for the PFR. However, none of these have developed a market model including both PFR and SFR. In this chapter, a comprehensive ED model with both primary and secondary frequency constraints is proposed and tested.
2.3 Frequency Control Process

The frequency control process in power systems can be categorized into the contingency control mode and normal control mode. In the normal control mode, the load fluctuates in a slow and relatively smooth variation. For most conditions, only the SFR is utilized by Automatic Generation Control (AGC) to compensate the resulting imbalance. The goal of the normal control mode is to maintain frequency within the certain band around the nominal frequency. The metrics used to measure the frequency performance in normal control mode are called Control Performance Standards 1 (CPS1) and Balancing Authority ACE Limit (BAAL) [27]. The frequency control after the loss of large generation is the frequency response in the contingency control mode which spans from a few seconds to several minutes. In the moment just after the contingency, some inertial energy of the on-line generators is released, effectively utilizing the stored kinetic energy of the rotating machines to arrest the frequency. The initial slope of the frequency drop depends on the loss of MW and the inertia of the entire interconnection. The speed governor does not respond to the frequency deviation immediately. Usually a bandwidth of several hundred mHz is set to avoid the unnecessary governor reaction to small frequency deviations. Under conditions where frequency deviation exceeds the bandwidth, the speed governor starts to adjust the valve position to arrest the further frequency drop. All on-line units which have active speed governors will respond to frequency drop based on their droop characteristics. After a few seconds, following initial action of the generation, a new generation/load balance is reached, and the frequency dips to its nadir. If the nadir falls below the any Under Frequency Load Shedding (UFLS) relays trigger frequency, load will be shed to achieve new power balance.
In most regions of North America, the standard load shedding scheme is comprised of three steps: 10% load is shed when frequency drops to 59.2 Hz, 15% load is shed when frequency drops to 58.8 Hz, and 20% load is shed when frequency drops to 58.0 Hz [28]. A sufficient amount of PFR, with enough ramping capability, can prevent activation of UFLS relays. Following the particular point in time that the frequency reaches the nadir, the frequency will oscillate for several seconds and finally settle to a steady state which is closer to the nominal frequency. After the settling point, the SFR will correct the frequency deviation, bringing the frequency back to its nominal value. The illustration of the frequency control process after the contingency is shown in Fig 2.1 [51].

![Fig 2.1 Frequency control process](image)

2.4 Adequacy of the Frequency Response

2.4.1 Frequency Nadir Time Estimation

During the first several seconds following a major loss of generation, there is no significant influence of PFR on the system, and the frequency drops at a constant Rate-of-
Change-of-Frequency (RoCoF). When frequency deviation exceeds the governor deadband $\Delta f_{db}$, the PFR will take action to decrease the RoCoF until it becomes zero at the nadir. The dynamic response of the speed governor and prime mover after the loss of generation is simplified according to the following assumptions:

1) The RoCoF during the first several seconds following loss of generation is assumed to be constant. Based on the power balance swing equation (2.1), the initial slope of frequency dip is computed as $S_0$ in (2.2) where $P_{loss}$ is the loss of generation in MW, $H$ is the system inertia in seconds, $f_0$ is the nominal frequency and $P_0$ is the base MVA:

$$\frac{2HP_0}{f_0} \cdot \frac{df}{dt} = \Delta P_m - \Delta P_e$$

(2.1)

$$S_0 = \frac{-P_{loss} \cdot f_0}{2H \cdot P_0}$$

(2.2)

2) For frequency deviations outside the dead-band, all the generators installed with speed governors are assumed to respond to the frequency deviation at their maximum short term ramp rate (STRR) until the time when the frequency reaches the nadir. Reference [29] gives a simplified governor-turbine model to demonstrate that generator output is very close to being linear over the time before the nadir is reached. With this assumption, the RoCoF is approximated to be a linear function as (2.3) during the time between when the dead-band frequency is reached and the time when the nadir frequency is reached. In (2.3), the $rr$ represents the short term ramping capability provided by the active governor. By integrating the RoCoF function, the frequency trajectory is calculated as (2.4) which is a quadratic function. Based on the calculated frequency trajectory, the minimum frequency can be
calculated as (2.5). In order to prevent the UFLS trigger, the minimum frequency should be no less than the UFLS threshold $\Delta f_{UFLS}$. The minimum ramping capability requirement can be derived on (2.6) for avoiding the UFLS trigger.

\[
\frac{df}{dt} = \frac{f_0}{2H \cdot P_0} (rr \cdot t - P_{loss}) \tag{2.3}
\]

\[
f(t) = \frac{f_0 \cdot rr}{4H \cdot P_0} t^2 + \frac{-P_{loss} \cdot f_0}{2H \cdot P_0} t + f_0 - \Delta f_{db} \tag{2.4}
\]

\[
f_{min} = f_0 - \Delta f_{db} - \frac{f_0 \cdot P_{loss}^2}{4H \cdot P_0 \cdot rr} \tag{2.5}
\]

\[
rr \geq \frac{f_0 \cdot P_{loss}^2}{4H \cdot P_0 (\Delta f_{UFLS} - \Delta f_{db})} \tag{2.6}
\]

For a given loss of generation, the minimum requirement on the ramping capability is equivalent to the maximum allowable time $t_{nadir}$ for arresting the frequency dip which is expressed as (2.7). From (2.7), it can be seen that the smaller the inertia $H$ is, and the larger the loss of generation $P_{loss}$ is, the is shorter time required to prevent the UFLS trigger frequency. So the required level of PFR should be the amount that can be fully deployed before $t_{nadir}$ to arrest the frequency deviation [30].

\[
t_{nadir} \leq \frac{4H \cdot P_0 (\Delta f_{UFLS} - \Delta f_{db})}{f_0 \cdot P_{loss}} + \frac{2H \cdot P_0 \cdot \Delta f_{db}}{f_0 \cdot P_{loss}} \tag{2.7}
\]

2.4.2 PFR Adequacy

In the traditional Economic Dispatch (ED) model, the reserve requirement is based only on capacity adequacy, i.e., the need to compensate for loss of a generation unit. However, the
insufficient reserve ramping capability can also impact frequency, e.g., an overly-long frequency arrest time or even an UFLS triggering. Given specification of the system inertia, generation loss, and governor dead-band, the maximum allowable time to prevent UFLS is given by (2.7). It can further be substituted into (2.8) to ensure not only sufficient capacity but also adequate ramping capability:

\[
\sum_i r_i \cdot t_{nadir} \geq P_{loss}
\]  

(2.8)

In the current industry practice, only the reserve capacity can be procured in the reserve market. So (2.8) is further converted into (2.9) and (2.10) to include the PFR capacity \( y_i \) as the decision variable. In 2011, FERC issued Order No.755 requiring the Independent System Operator (ISO) to modify the compensation mechanism to include a performance payment in addition to the existing capacity payment [31]. Although the generation is only compensated based on their ex-post performance, each generator could also price its reserve in the ex-ante market based on its ramping capability. Because every generator has a time delay in responding to the frequency deviation, it is assumed the time delay is reflected in the average ramp rate, and the generators are responsible to provide the average ramp rate information to the ISO based on their field tests.

\[
y_i \leq r_i \cdot t_{nadir}
\]  

(2.9)

\[
\sum_i y_i \geq P_{loss}
\]  

(2.10)

Besides the PFR capacity and ramp rate requirement, the deliverability is also a key factor to be considered in scheduling. The transmission constraint should not be violated
even when the PFR are fully deployed. The adaptive transmission rate (ATR) [32] is used in equation (2.11) as the relaxed transmission flow limit for a short period of time after the contingency. In (2.11), \( SF_{li} \) is the shift factor of bus \( i \) on line \( l \), \( g_i \) is the base dispatch target, \( d_i \) is the forecasted demand in each bus and \( f_i \) is the line flow limit.

\[
\sum_i SF_{li} \left( g_i + y_i - d_i \right) \leq f_{i,\text{ltge}} 
\]  

(2.11)

### 2.4.3 SFR Adequacy

After the PFR functions to arrest the frequency, settling it at the steady-state (SS), the PFR action begins to reduce, and the SFR starts to take action to correct the steady-state error and move the frequency back to the nominal value. According to the NERC B1 criterion, a control area is required to return Area Control Error (ACE) to zero within 10 minutes after the contingency. So the SFR should not only have enough capacity to compensate the generation/load imbalance but also enough ramping capability to meet the NERC B1 criterion. At the steady state, the frequency deviation can be calculated by (2.12) and the steady state ACE can be calculated by (2.13) in which the \( R \) is the governor droop characteristic. The ACE signal is then sent to each participating regulation generator by a pre-determined participating factor. During the 10 minutes, the wind power and load may also deviate. So the net load variation (\( \Delta d - \Delta w \)) in 10 minute should also be considered in the SFR requirement. With this consideration, we add an extra term into total ACE as indicated in (2.14) to obtain the extra SFR action required by the net load deviation.

\[
\Delta f_{ss} = -P_{\text{lost}} \frac{f_0 \cdot R}{P_0} 
\]  

(2.12)
\[ ACE_{st} = \Delta f_{st} \cdot \frac{1}{R} \] (2.13)

\[ ACE_{tot} = ACE_{st} + \Delta w - \Delta d \] (2.14)

The adequacy of SFR requires enough SFR capacity \( r_i \) to cover the total ACE (2.15) while subject to the units long term ramp rate \( RR_i \) (2.16). The transmission line constraint (2.17) should also be included to respect the line flow limit.

\[-ACE_{tot} \leq \sum_i r_i \] (2.15)

\[ r_i \leq 10RR_i \] (2.16)

\[ \sum_i SF_i(g_i + r_i + w_i + \Delta w_i - d_i - \Delta d_i) \leq f_i \] (2.17)

### 2.5 Frequency Constrained Economic Dispatch Model

With the PFR and SFR adequacy constraints mentioned above, the traditional ED model is modified to include these constraints to obtain a better frequency performance. The proposed frequency constrained ED (FC-ED) model is formulated as follows:

\[
\text{minimize} \quad \sum_i C_i(g_i) + \sum_i C_i(y_i) + \sum_i C_i(r_i) + 1000s_i
\] (2.18)

subject to

\[
\sum_i g_i + \sum_i w_i = d
\] (2.19)

\[
\sum_i SF_i(g_i + w_i - d_i) \leq f_i
\] (2.20)

\[
w_i \leq w_f
\] (2.21)

\[
g_i + y_i + r_i \leq \overline{g}_i
\] (2.22)
\[ g_i - r_i \geq g_i \]  \hspace{1cm} (2.23)

\[ y_i \leq r_i \cdot t_{nadir} \]  \hspace{1cm} (2.24)

\[ \sum_i y_i + s_i \geq P_{loss} \]  \hspace{1cm} (2.25)

\[ \sum_i SF_l (g_i + y_i + w_i - d_i) \leq f_{\text{ctgc}} \]  \hspace{1cm} (2.26)

\[ r_i \leq 10RR_i \]  \hspace{1cm} (2.27)

\[ \sum_i r_i \geq -ACE_{\text{tot}} \]  \hspace{1cm} (2.28)

\[ \sum_i SF_l (g_i + r_i + w_i + \Delta w_i - d_i - \Delta d_i) \leq f_i \]  \hspace{1cm} (2.29)

where (2.18) is the objective function which minimize the energy cost and reserve cost. Equation (2.19) is the power balance equation. Equation (2.20) is the DC power flow constraint under normal condition. Equation (2.21) is the generation limit of wind power subject to the wind forecast \( wf \). Equation (2.22) and (2.23) are the upper and lower capacity limit constraints of generators. Equation (2.24) is the PFR capacity limit subject to unit’s Short Term Ramp Rate (STRR) and nadir time. Equation (2.25) is the PFR adequacy requirement to cover the loss of generator where the slack variable \( s_1 \) is introduced to penalize the constraint violation at the cost of $1000/MW. Equation (2.26) is the transmission constraint under contingency condition. Equation (2.27) is the maximum SFR capacity limit subject to Long Term Ramp Rate (LTRR). Equation (2.28) is the SFR adequacy requirement to zero ACE in 10 minutes. Equation (2.29) is the transmission constraint at 10 minutes after the contingency when the power injection may differ from the
initial value. The problem is a linear programming problem and is very computational efficient for large system.

2.6 Case Study

2.6.1 PJM 5 bus system

The PJM 5 bus system is simulated to evaluate the performance of the proposed model. The system data is given in [33] and illustrated in Table 2.1 where the bidding price for energy and reserve are both given. The reserve price not only reflects the reserve opportunity cost but also the ramping capability. Also the generators’ STRR and LTRR are provided by each generator in units MW/sec and MW/min. The transmission system topology is plotted in Fig 2.2. The total load is distributed to area 2, 3 and 4 with 20%, 40% and 40% distribution factor. The wind plant is located at area 2 and could also be distributed to different buses in the same fashion as the load is. The FC-ED model is developed in GAMS [34] and solved by CPLEX LP solver. The contingency event is a loss of 30MW generation which is about 3% of total load. The system total inertial is pre-known since the unit ON/OFF status is fixed. There is a 1.2% variation in load and wind during the time period of 10 min. The governor deadband is set at 0.036 HZ and the first UFLS threshold is set at 0.4 HZ. The MATLAB/SIMULINK model is built up to compare the frequency performance between traditional ED and FC-ED. In the MATLAB/SIMULINK model, the reheat steam turbine is modeled to represent the dynamic frequency response of the whole system in Fig 2.3[6]. The load damping is also included in MATLAB/SIMULINK to provide a better frequency performance, but it is not included in the FC-ED model so that the FC-ED provides a more conservative and reliable solution. The FC-ED result is shown in Table II which includes the
energy dispatch, PFR dispatch and SFR dispatch. The Locational Marginal Price (LMP) for energy and Market Clearing Price (MCP) for each type of reserve are also shown in Table 2.2. From Table 2.2, it is observed that bus D and E have the highest energy cost, so the energy dispatch for D and E are closer to the lower capacity limit. Although the PFR and SFR cost at bus D and E are higher than the others, they are still dispatched more PFR and SFR due to their higher LTRR and STRR ramping capability.

Table 2.1 5 Bus Generator Input Data

<table>
<thead>
<tr>
<th>Bus</th>
<th>$P_{\text{min}}$ (MW)</th>
<th>$P_{\text{max}}$ (MW)</th>
<th>$C_{E}$ ($)</th>
<th>$C_{\text{PFR}}$ ($)</th>
<th>$C_{\text{SFR}}$ ($)</th>
<th>LTRR (MW/min)</th>
<th>STRR (MW/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>40</td>
<td>110</td>
<td>14</td>
<td>10</td>
<td>5</td>
<td>2</td>
<td>0.5</td>
</tr>
<tr>
<td>B</td>
<td>200</td>
<td>600</td>
<td>10</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0.25</td>
</tr>
<tr>
<td>C</td>
<td>40</td>
<td>100</td>
<td>15</td>
<td>8</td>
<td>4</td>
<td>2</td>
<td>0.5</td>
</tr>
<tr>
<td>D</td>
<td>100</td>
<td>520</td>
<td>28</td>
<td>16</td>
<td>4</td>
<td>5</td>
<td>1.25</td>
</tr>
<tr>
<td>E</td>
<td>50</td>
<td>200</td>
<td>40</td>
<td>20</td>
<td>10</td>
<td>10</td>
<td>3.75</td>
</tr>
</tbody>
</table>

Table 2.2 Results of PJM 5 Bus System

<table>
<thead>
<tr>
<th>Bus</th>
<th>Energy (MW)</th>
<th>PFR (MW)</th>
<th>SFR (MW)</th>
<th>LMP ($)</th>
<th>PFR MCP ($)</th>
<th>SFR MCP ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>106.96</td>
<td>3.04</td>
<td>0</td>
<td>16.28</td>
<td>20</td>
<td>4</td>
</tr>
<tr>
<td>B</td>
<td>417.27</td>
<td>1.52</td>
<td>10</td>
<td>24.75</td>
<td>20</td>
<td>4</td>
</tr>
<tr>
<td>C</td>
<td>96.96</td>
<td>3.04</td>
<td>0</td>
<td>28.00</td>
<td>20</td>
<td>4</td>
</tr>
<tr>
<td>D</td>
<td>291.51</td>
<td>7.60</td>
<td>0</td>
<td>36.95</td>
<td>20</td>
<td>4</td>
</tr>
<tr>
<td>E</td>
<td>50.00</td>
<td>14.79</td>
<td>32</td>
<td>10.00</td>
<td>20</td>
<td>4</td>
</tr>
</tbody>
</table>
In report [35], several frequency performance metrics are proposed to study the frequency response in California ISO (CAISO). Some of them are utilized in this chapter to compare the frequency performance between ED and FC-ED. They are summarized as follows:

1) Frequency Nadir: The Frequency Nadir is the point where the frequency reaches its minimum point.
2) Frequency Nadir Time: Frequency Nadir Time is the time when the frequency reaches its minimum point.

3) Nadir-based Frequency Response: The Nadir-based Frequency Response is the size of the contingency divided by the change of frequency at nadir. The unit is normalized to MW/0.1HZ.

4) Settling Frequency: The Settling Frequency is the frequency measured at steady state point, usually around 50-60 seconds. It is assumed that before the settling point, only PFR respond to the frequency deviation, after then, the SFR began to act and return the frequency to nominal.

5) Settling Time: Settling time is the time when the frequency reaches the steady state point.

Table 2.3 Key Frequency Performance Metrics for 5-Bus system

<table>
<thead>
<tr>
<th></th>
<th>FC-ED</th>
<th>Traditional ED</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nadir (HZ)</td>
<td>59.628</td>
<td>59.01</td>
</tr>
<tr>
<td>Nadir Time (s)</td>
<td>4.7</td>
<td>14.1</td>
</tr>
<tr>
<td>Nadir Based Frequency Response (MW/0.1HZ)</td>
<td>8.06</td>
<td>3.03</td>
</tr>
<tr>
<td>Settling Frequency (HZ)</td>
<td>59.91</td>
<td>59.91</td>
</tr>
<tr>
<td>Settling Time (s)</td>
<td>34.8</td>
<td>&gt;100</td>
</tr>
</tbody>
</table>
Fig 2.4 Frequency performance between ED (dashed) and FC-ED (solid) with 5 bus

The frequency dynamics within 50s is plotted in Fig 2.4 and summarized in the Table 2.3. It is shown that FC-ED presents a better frequency performance from various metrics. The frequency nadir is 59.628 HZ with FC-ED comparing to 59.01 HZ with traditional ED which is far below UFLS triggering frequency. The nadir time is about 4.7s with FC-ED which is much shorter than 14.1s with traditional ED. For the Nadir based Frequency Response, the FC-ED provides the PFR at an average of 8.06MW/0.1HZ up to the nadir point, while with ED the PFR is only provided at 3.03 MW/0.1HZ. The settling time with FC-ED is about 35s comparing to more than 100s with ED. The total operation cost for FC-ED is $17,894 in comparison with $17,474 with traditional ED. The better frequency performance comes along with the comparable operation cost from the FC-ED shows its advantage by including frequency related constraints in the ED model.
2.6.2 IEEE 118 bus system

The IEEE 118 bus system comprises 54 generators, 186 lines and 91 demands. The system peak load is about 3733 MW at hour 15. The system data is from [36]. The system is first solved by a Security Constrained Unit Commitment (SCUC) application to select committed online units, resulting in 23 out of 54 generators being committed online as the input for the proposed FC-ED model. We assume a sudden loss of a 210 MW generator occurs at $t_0$ which is about 5.6% of the peak load. The dead-band is set to 0.036 Hz, and the UFLS threshold is set to 0.5 Hz to provide a reasonable margin above the NERC UFLS threshold. The initial RoCoF is about -0.237 HZ/s and the forecasted nadir time is about 4.07s. A $1000 PFR scarcity price is set to penalize the PFR requirement constraint violation. The system LMP is 13.315 $/MW and PFR MCP is 1000 $/MWh due to the 2 MW violation of the PFR requirement constraint (2.25). The SFR MCP is only about 5.41 $/MWH which is much lower than PFR price. The comparison of frequency performance between traditional ED and FC-ED is plotted in Fig 2.5, and the key performance metrics are summarized in Table 2.4. It is again shown that with FC-ED, the various frequency performance metrics are much better than those with the traditional ED. The total operation cost for FC-ED model is $51,295 which is about 10% higher than $ 46,861 total operation cost with traditional ED due to the penalty cost of PFR requirement constraint violation. The PFR requirement constraint violation indicates the insufficient ramp rate and insufficient inertia from the online units to recover the severe frequency deviation and it can be overcame by a combined FC-SCUC-ED model which will be proposed in the next chapter.
Table 2.4  Key Frequency Performance Metrics for 118 Bus System

<table>
<thead>
<tr>
<th></th>
<th>FC-ED</th>
<th>Traditional ED</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nadir (HZ)</td>
<td>59.573</td>
<td>58.33</td>
</tr>
<tr>
<td>Nadir Time (s)</td>
<td>4.6</td>
<td>19.4</td>
</tr>
<tr>
<td>Nadir Based Frequency Response (MW/0.1HZ)</td>
<td>49.2</td>
<td>12.6</td>
</tr>
<tr>
<td>Settling Frequency (HZ)</td>
<td>59.88</td>
<td>59.88</td>
</tr>
<tr>
<td>Settling Time (s)</td>
<td>39</td>
<td>&gt;100</td>
</tr>
</tbody>
</table>

Fig 2.5 Frequency Performance between ED (dashed) and FC-ED (solid) with 118 bus

2.7 Conclusion

With the comparison between traditional ED and FC-ED, it was found the FC-ED gives a better frequency performance in terms of various frequency metrics such as nadir frequency,
nadir time, nadir based frequency response and settling time. The proposed FC-ED provides the possibility to incentivize alternative resources such as renewable energy, storage and demand response to provide the high quality frequency response reserve.

As penetration of intermittent resources increase, the system inertia will decrease so that the RoCoF will be steeper after the loss of generation and the online conventional units may not have sufficient short term ramping capability to arrest the frequency above the UFLS triggering point. In this case, more units need to be turned on to increase system rotating inertial and short term ramping capability. In the next chapter, we will investigate the connection between the FC-ED and Unit Commitment problem. The FC-UC-ED model will solve the UC and FC-ED problem as the master problem and sub-problem. The inertial and ramping capability insufficiency in the FC-ED sub-problem will generate the necessary feasibility constraints back into UC master problem to make sure the sufficient units are online to support the frequency stability.
CHAPTER 3 STOCHASTIC UNIT COMMITMENT WITH INERTIAL, PRIMARY AND SECONDARY FREQUENCY CONSTRAINTS

3.1 Introduction

Under the high penetration of wind and solar, the system frequency performance is expected to be degrading and the current frequency response reserve is more likely to be insufficient because of the following reasons: Firstly, wind and solar are incentivized to maximize power production, and grid codes allow this, so they are not operated to provide the IR, PFR and SFR; Secondly, the wind and solar have zero fuel cost in contradictory to conventional thermal unit so they are preferred to dispatch at their full available capacity unless the network is congested. That means wind and solar will incur a high opportunity cost to back down the generation for providing the frequency response reserve; thirdly, the wind and solar are more variable and uncertain than the conventional thermal units, so even more frequency responsive reserve is required than before. Under this background, the unit commitment scheme has to rely on the remaining thermal units and demand side response to provide sufficient frequency response reserve.

The current reserve market design mainly consists of four types of products: regulation up, regulation down, spinning and non-spinning reserve. Regulation up and regulation down are belong to SFR mainly used for frequency control under normal condition, the spinning and non-spinning reserve are the SFR mainly used under contingency scenario. There is currently no market product for IR and PFR in US. In this chapter, the stochastic unit commitment with IR, PFR and SFR constraints is developed to procure sufficient IR, PFR and SFR to meet the frequency performance requirement under various generation
contingencies and load/wind ramping scenarios. The sufficiency of the IR and PFR ensures the frequency drop after contingency will not trigger unnecessary Under Frequency Load Shedding (UFLS) and the sufficiency of SFR ensures Area Control Error (ACE) is recovered to nominal within allowable time period.

3.2 Inertia and Primary Frequency Reserve Requirement

The full model to represent the governor-turbine dynamic behavior has been extensively studied in the literature. In those models, different types of generators are modelled by various governor-turbine control system models which are of high-order and complexity. In order to capture the frequency dynamic within the market dispatch model as a set of equality and inequality constraints without introducing excessive complexity and computational burden, some simplification and approximation are applied:

1) All the governors and turbines in the power system are aggregated to be one equivalent governor-turbine set.

2) Inertia from different generators is lumped into one equivalent system inertia.

3) The first-order simplified governor-turbine model is used to estimate the frequency trajectory after contingency.

4) The load damping effect is assumed to be negligible relative to the generator governor response.

Based on the above simplification, the power balance swing equation can be expressed as (3.1):

\[
\frac{2H_{sys}}{f_0} \frac{d\Delta f}{dt} = \frac{\Delta P_m - \Delta P_f}{S_{B,sys}}
\]
where $\Delta P_m$ is the mechanical power output change, $\Delta P_e$ is the electrical power output change, $\Delta f$ is the system frequency deviation, $S_{B,sys}$ is the system base MVA and $H_{sys}$ is the system inertia constant in s. Assuming after the generation contingency, the governor and turbine output are maintained constant, then the initial power imbalance equals the contingency $P_{loss}$. The initial Rate of Change of Frequency (RoCoF) is calculated as (3.2):

$$S_0 = \frac{-P_{loss} \cdot f_0}{2H_{sys}}$$

(3.2)

It can be observed from (3.2) that the initial RoCoF is dependent on the size of contingency $P_{loss}$ and the system inertia $H_{sys}$. Given the size of contingency, the higher the system inertia, the less steep is the RoCoF which results in increased time for PFR to respond; consequently, the frequency nadir is higher and less likely to cause UFLS. The system inertia is the sum of the inertia from all the online units and it can be calculated as (3.3) where $H_i$ is the inertia constant of unit $i$, $P_{max}^i$ is the unit maximum capacity, $I_i$ is the unit ON/OFF status and $S_{B,sys}$ is the system MVA base:

$$H_{sys} = \sum_{i \in k} H_i P_{max}^i I_i$$

(3.3)

Assuming the unit $i$ responds at its maximum short term ramp rate $rr_i$ after the loss of generation [4][29], the frequency trajectory is governed by the differential equation (3.4) by substituting unit short term ramp rate $rr$ into (3.1) where $rr = \sum_i rr_i$ :

$$\frac{2H_{sys}}{f_0} \frac{d\Delta f}{dt} = \frac{rr \cdot t - P_{loss}}{S_{B,sys}}$$

(3.4)
By integrating the differential equation (3.4), the frequency trajectory can be expressed as (3.5):

\[ f(t) = \frac{f_0 rr}{4H_{sys} S_{B,sys}} t^2 - \frac{P_{loss} f_0}{2H_{sys} S_{B,sys}} t + f_0 \]  

(3.5)

For simplicity, the governor dead-band is not modelled in the frequency trajectory equation, but it can be easily included if necessary. It can be observed that the frequency trajectory can be expressed as a quadratic function of time \( t \) with the assumption of linear governor response. So the frequency nadir and nadir time can be calculated as (3.6) and (3.7):

\[ f_{\min} = f_0 - \frac{f_0 P_{loss}^2}{4H_{sys} S_{B,sys} rr} \]  

(3.6)

\[ t_{\min} = \frac{P_{loss}}{rr} \]  

(3.7)

In order to avoid the UFLS event, the unit short term ramp rate should be greater than (3.8):

\[ rr \geq \frac{f_0 P_{loss}^2}{4H_{sys} S_{B,sys} (f_0 - f_{UFLS})} \]  

(3.8)

In other words, the nadir time \( t_{nadir} \) should be less than (3.9) by substituting (3.8) into (3.7):

\[ t_{nadir} \leq \frac{4H_{sys} S_{B,sys} (f_0 - f_{UFLS})}{f_0 P_{loss}} \]  

(3.9)

Inequality (3.9) can be understood in such way: given the size of loss of generation, the initial RoCoF is certain, the longer it takes the unit to respond to frequency excursion, the
lower will be the frequency nadir. In order to avoid the UFLS event, the units have to respond fast enough to arrest the frequency excursion before \( t_{nadir} \).

Based on the maximum allowable nadir time calculated from (3.9), the maximum primary frequency reserve the unit can provide is computed as (3.10):

\[
y_i \leq r_i \frac{4H_{sys}S_{b,sys} (f_0 - f_{UFLS})}{f_0 P_{loss}} \quad \forall i \neq k
\]  

The total primary frequency reserve must be greater than the single most severe contingency, which in this chapter, is the capacity of the largest generator. If all the available primary frequency reserve is not able to arrest the frequency above the UFLS point, some involuntary load shedding will occur to recover the frequency. The primary frequency reserve requirement is expressed as (3.11) where the \( l_{S,d} \) is the involuntary load shedding and there is a high penalty cost associated with it and reflected in the total operation cost.

\[
\sum_{i \neq k} y_i + \sum_{d} l_{S,d} \geq P_{loss}
\]  

(3.11)

Besides the PFR capacity and ramp rate requirement, the deliverability is also a key factor to be considered in scheduling. The transmission constraint should not be violated even when the PFR are fully deployed. The adaptive transmission rate (ATR) is used in post-contingency power flow constraints (3.12) where power flow limit is relaxed to its contingency limit, often referred to as its emergency rating.

\[
\sum_b S_{F,i,b} \left[ A_{b,i} (P_i + y_i) + B_{b,w} P_w - C_{b,d} (P_d - l_{S,d}) \right] \leq P^\text{max}_{\text{ctgc}}
\]  

(3.12)
3.4 Secondary Frequency Reserve Requirement

After the PFR arrest the frequency decay and stabilize it for the steady state, the SFR starts to function to recover the frequency back to its nominal value. According to the NERC requirement DCS R4 [37], the Balancing Authority should return the ACE back to zero or pre-contingency value within 15 minutes. The contingency based spinning and non-spinning reserve is required to deploy within 10 minutes. So we use 10 minutes in this chapter as the longest allowable time to recover the ACE which is stricter than the NERC DCS requirement. At the steady state, the frequency deviation $\Delta f_{ss}$ can be calculated as (3.13) and the steady-state ACE ($ACE_{ss}$) can be calculated as (3.14). Within 10 minutes, the load and wind can also significantly deviate from their original value especially under high wind penetration scenario. So the load variation $\Delta P_d$ and wind variation $\Delta P_w$ are also considered in the total ACE ($ACE_{tot}$) which needs to be corrected in 10 minutes. The total ACE calculated in (3.15) is then sent to each regulation unit by some pre-determined participating factor.

$$\frac{\Delta f_{ss}}{f_0} \frac{S_{B,sys}}{R} = -P_{loss}$$  \hspace{1cm} (3.13)

$$ACE_{ss} = \Delta f_{ss} \left( \frac{1}{R} + D \right)$$  \hspace{1cm} (3.14)

$$ACE_{tot} = ACE_{ss} + \Delta P_w - \Delta P_d$$  \hspace{1cm} (3.15)

Besides the SFR capacity used for contingency scenario, a sufficient amount of regulation reserve should also be procured for covering the minute to minute load and wind fluctuation in normal operation condition. The regulation reserve requirement is set as 1% of peak load in peak hours and 1% of valley load in off-peak hours according to PJM system.
practice. In next chapter, we present a new method in determining the regulation reserve requirement and the new method can be used to replace the PJM practice. In the contingency condition, the regulation reserve can be temporarily used to substitute the spinning and non-spinning reserve if they are scarce. The market clearing price of regulation reserve is usually higher than spinning and non-spinning reserve because of the substitution effect. Besides the conventional generator, the demand response resources can also be used to provide the SFR. The demand response resource is allowed to participate in the ancillary service market like the conventional generator does.

Not only can the on-line units provide the SFR, some off-line quick-start units can also provide the non-spinning SFR as shown in (3.16) if the unit is able to turn on in 10 minutes.

\[ N_i \leq QSC_i (1 - I_i) \quad \forall i \quad (3.16) \]

The constraints (3.17)-(3.19) below represents the constraints related to SFR requirement. In these constraints, (3.17) requires the total amount of regulation reserve, spinning SFR, non-spinning SFR and demand response should be sufficient to correct the total ACE after loss of generation. Equation (3.18) requires at least half of total SFR should come from on-line generating units. Similar to the transmission flow constraint (3.17) for PFR, the SFR is also subject to the power flow constraint as shown in (3.19).

\[ \sum_{i \neq k} (r_i + z_i + n_i) + \sum_d d_{rd} \geq ACE_{tot} \quad (3.17) \]

\[ \sum_{i \neq k} r_i + \sum_{i \neq k} z_i \geq \frac{1}{2} ACE_{tot} \quad (3.18) \]
\[
\sum_{b} SF_{i,b} \left[ A_{b,i} (P_i + r_i + z_i + n_i) + B_{b,w} (P_w + \Delta P_w) \right] \leq P_{i}^{\text{max}} \quad \forall l \quad (3.19)
\]

### 3.5 Stochastic Unit Commitment with Frequency Constraints

The above proposed frequency related constraints can be integrated into the stochastic unit commitment model where the stochastic features are that each generator is associated with a contingency scenario, and the load and wind ramping are uncertain. The objective function (3.20) is aimed to minimize the total cost including first stage cost and second stage cost. The first stage cost includes the unit start-up/shut-down cost, unit dispatch cost, PFR procurement cost, SFR procurement cost and regulation procurement cost. The second stage cost includes the penalty cost for involuntary load shedding and the cost associated with demand response.

\[
\begin{align*}
\text{Minimize} & \quad \sum_{i} \sum_{t} \left[ N_i \cdot I_{i,t} + SU_i \cdot U_{i,t} + SD_i \cdot D_{i,t} \right. \\
& \quad \left. + C_y (P_{i,t}) + C_y (Y_{i,t}) + C_r (R_{i,t}) + C_z (Z_{i,t}) + C_n (N_{i,t}) \right] \\
& \quad + \sum_s pr_s \sum_{t} \sum_{d} \left[ C_{ls} (ls_{d,t,s}) + C_{dr} (dr_{d,t,s}) \right] \\
& \quad \sum_{i} P_{i,t} + \sum_{w} P_{w,t} = \sum_{d} P_{d,t}^{f} \quad \forall t \quad (3.21) \\
& \quad P_{w,t} \leq P_{w,t}^{f} \quad \forall w, t \quad (3.22) \\
& \quad P_{i,t} + Y_{i,t} + R_{i,t} + Z_{i,t} \leq P_{i}^{\text{max}} I_{i,t} \quad \forall i, t \quad (3.23) \\
& \quad P_{i,t} - R_{i,t} \geq P_{i}^{\text{min}} I_{i,t} \quad \forall i, t \quad (3.24)
\end{align*}
\]
\[ \sum_{i} R_{i,t} \geq 0.01 \sum_{d} P_{d,t} \quad \forall t \] (3.25)

\[ R_{i,t} \leq 5RR_i \quad \forall i, t \] (3.26)

\[ Z_{i,t} \leq 10RR_i \quad \forall i, t \] (3.27)

\[ N_{i,t} \leq QSC_i (1 - I_{i,t}) \quad \forall i, t \] (3.28)

\[ U_{i,t} - D_{i,t} = I_{i,t} - I_{i,t-1} \quad \forall i, t \] (3.29)

\[ U_{i,t} + D_{i,t} \leq 1 \quad \forall i, t \] (3.30)

\[ P_{i,t} - P_{i,t-1} \leq \left(1 - I_{i,t} \left(1 - I_{i,t-1}\right)\right)RR_i + I_{i,t} \left(1 - I_{i,t-1}\right)P_{i}^{\min} \quad \forall i, t \] (3.31)

\[ P_{i,t-1} - P_{i,t} \leq \left(1 - I_{i,t-1} \left(1 - I_{i,t}\right)\right)RR_i + I_{i,t-1} \left(1 - I_{i,t}\right)P_{i}^{\min} \quad \forall i, t \] (3.32)

\[ \left[ X_{i,t-1}^{ON} - T_{i}^{ON}\right] [I_{i,t-1} - I_{i,t}] \geq 0 \quad \forall i, t \] (3.33)

\[ \left[ X_{i,t-1}^{OFF} - T_{i}^{OFF}\right] [I_{i,t} - I_{i,t-1}] \geq 0 \quad \forall i, t \] (3.34)

\[ y_{i,t,s} \leq r_t \frac{4H_{\text{sys},s} S_{B,\text{sys}} \left(f_0 - f_{\text{UFLS}}\right)}{f_0 P_{\text{loss},s}} \quad \forall i \neq k, \forall s, \forall t \] (3.35)

\[ \sum_{i \neq k} y_{i,t,s} + \sum_{d} l_{s,d,t,s} \geq P_{\text{loss},s} \quad \forall i \neq k, \forall s, \forall t \] (3.36)

\[ \sum_{b} SF_{l,b} \left( A_{b,l} (P_{i,t} + y_{i,t,s}) + B_{b,l} P_{d,t} \right) \leq P_{i,t}^{\max} \quad \forall l, \forall s, \forall t \] (3.37)

\[ \sum_{i \neq k} (z_{i,t,s} + r_{i,t,s} + n_{i,t,s}) + \sum_{d} d_{i,t,d,s} \geq ACE_{\text{tot},s} \quad \forall s, \forall t \] (3.38)
The equation (3.21) is the power balance equation, (3.22) is the maximum dispatch-able wind constraint, (3.23) and (3.24) are the unit upper and lower capacity limit considering the reserve margin, (3.25) is the regulation reserve requirement, (3.26) is the regulation reserve capacity limit subject to 5 minute ramp rate limit, and (3.27) is the spinning reserve capacity limit subject to 10 minute ramp rate. Equation (3.28) is the capacity limit for non-spinning reserve. Equation (3.29) and (3.30) are unit ON/OFF status constraints, (3.31) and (3.32) are unit ramp-up/ramp-down constraints, (3.33) and (3.34) are unit minimum up-time/down-time constraints, (3.35)-(3.37) are the constraints associated with PFR and (3.38)-(3.40) are the constraints associated with SFR. The equation (3.41) limits the second stage actual reserve usage subject to first stage reserve capacity procurement. The constraints (3.35)-(3.41) are scenario dependent in which the $H_{sys,s}$, $ACE_{tot,s}$, $\Delta P_{d,t,s}$, $\Delta P_{w,t,s}$ and $P_{loss,s}$ are uncertain parameters dependent on scenario $s$, and $r_{i,t,s}$, $y_{i,t,s}$, $z_{i,t,s}$, $n_{i,t,s}$, $ls_{d,t,s}$ and $dr_{d,t,s}$ are scenario based second stage decision variables.

The scenario generation process consists of three components: the generation outage scenario, the wind variation scenario and load variation scenario. The probability of a single
scenario is the combined probability of three components. It is also assumed that once a generator is tripped, it will not be turned back on within 24 hours since the repair time is usually much longer than 24 hours. The Mean Time to Failure (MTTF) or Mean Time to Repair (MTTR) for a specific unit is assessed based on its historical outage record. It is widely accepted that the time between two consecutive failures follows the exponential distribution of MTTF, as does the time between two consecutive repairs [38]. So based on the given MTTF, the probability of the unit outage within hour \( \tau \) can be calculated as (3.42):

\[
\Pr(k, \tau) = \int_{\tau-1}^{\tau} \lambda_k e^{-\lambda_k t} dt = e^{-\lambda_k \tau} \left( e^{\lambda_k} - 1 \right)
\]

where \( \lambda_k \) is the failure rate of the stochastic process and equals the inverse of MTTF of contingency \( k \). The probability of no contingency \( k \) happen within 24 hour can be calculated as (3.43):

\[
1 - \int_{0}^{24} \lambda_k e^{-\lambda_k t} dt = e^{-\lambda_k 24}
\]

The 10 minutes load and wind ramping are represented by a normal distribution based on the historical load and wind ramping. The Latin Hypercube Sampling (LHS) method [39] is used to generate the wind and load ramping scenario and the probability of each load and wind variation scenario is assigned as inverse of the number of scenarios.

### 3.6 Solution Methodology

The stochastic problem is computationally expensive due to its significant size with a large number of scenarios. And it has some complicating variables which do not allow us to solve the problem by block separation. The L-shape method provides us with an algorithm to
solve the problem with complicating variables by iterative fashion [40]. The problem is decomposed into a first stage master problem and several second stage sub-problems where each sub-problem represents a single scenario problem.

The two stage stochastic optimization can be abstracted and formulated as follows:

\[
\text{Minimize } \quad z = C^T x + \sum_s p_r D^T y_s \\
\text{ s.t. } \quad Ax \leq b \\
\quad \quad \quad \quad \quad \quad \quad \quad Tx + W y_s \leq h_i \quad \forall s \in S \\
\quad \quad \quad \quad \quad \quad \quad \quad x \geq 0, \quad y_s \geq 0
\]  

where \( C \in R^{n_1} \), \( b \in R^{m_1} \) and \( D \in R^{n_2} \) are the known vectors, \( A \in R^{m_1 \times n_1} \), \( T \in R^{m_2 \times n_1} \) and \( W \in R^{m_2 \times n_2} \) are the known matrices. \( h_i \in R^{m_2} \) is the uncertainty vector, \( x \in R^{n_1} \) is the first stage decision variable, \( y_s \in R^{n_2} \) is the second stage decision variable, \( p_r \in R \) is the probability of each scenario \( s \), \( S \) is the uncertainty set. The L-shape algorithm, otherwise known as Benders Decomposition is illustrated as follows:
Algorithm: L-Shaped Method

1) Solve the master problem (3.45) and get the lower bound solution $z_{\text{lower}}$ at $\hat{x}$ and $\hat{Q}_s$. Since in the first iteration, $Q_s$ is unconstrained, so simply let $\hat{Q}_s$ be $-\infty$, only minimize over the constrained variable $x$.

2) For $\forall s \in S$ Do:

If the sub-problem (3.46) is infeasible, then let $\hat{u}_s$ be the extreme ray of the dual of (3.46), and generate the feasibility cut (3.47).

Else If $p_s D^T \hat{y}_s > \hat{Q}_s$, then $\hat{Q}_s$ is the unrealistic estimation of $p_s D^T y_s$, then a optimality cut (3.48) is generated where $\hat{u}_p$ is the optimal solution of the dual of (3.46).

1) Solve the updated master problem (3.49) and get the new lower bound solution $z_{\text{lower}}$ at $\hat{x}$ and $\hat{Q}_s$. Go to step 2 again, if there is no feasibility cut and optimality cut generated, $x^*$ and $Q^*_s$ are the optimal solution.

\[
\begin{align*}
\text{Minimize} & \quad z = C^T x + \sum_s Q_s \\
\text{s.t.} & \quad Ax \leq b \\
& \quad x \geq 0
\end{align*}
\]

(3.45)

\[
\begin{align*}
\text{Minimize} & \quad D^T y_s \\
\text{s.t.} & \quad W y_s \leq h_s - T \hat{x} \\
& \quad y_s \geq 0
\end{align*}
\]

(3.46)

\[
\begin{align*}
\hat{u}_s^T T x \leq h_s^T \hat{u}_s \\
p_s (h_s - T x)^T \hat{u}_p \leq Q_s
\end{align*}
\]

(3.47)

(3.48)

\[
\begin{align*}
\text{Minimize} & \quad z = C^T x + \sum_s Q_s \\
\text{s.t.} & \quad \hat{u}_s^T T x \leq h_s^T \hat{u}_s \\
& \quad p_s (h_s - T x)^T \hat{u}_p \leq Q_s \\
& \quad Ax \leq b \\
& \quad x \geq 0
\end{align*}
\]

(3.49)
3.7 Numerical Case Study

A PJM 5 bus system and IEEE 118 bus system are tested to demonstrate the effectiveness of proposed model. The model is developed in GAMS 23.4.3 and solved by the IBM ILOG CPLEX 12.1.0 on an Intel Core i5 2.60-GHz personal computer.

3.7.1 PJM 5 bus system

The PJM 5 bus system is used to test the proposed model. The system includes 5 aggregated generators, 6 lines, 3 loads and one wind farm located at bus 1. The single most severe contingency is the trip of a 40 MW generator at bus 1. Assuming the 40-MW generator is the most economical base load unit so it is always ON during the entire schedule period. The generator characteristic data is given from Table 3.1 and the transmission topology is illustrated in Fig 3.1. The wind penetration level is about 20% of the hourly load. And the 10 minute load and wind ramping event is generated based on the historical California ISO (CAISO) 1 minute wind output data [16]. Among 5 generators, three of them have the quick start capability which allow the unit to switch from OFF to ON in 10 minutes. Four different cases are studied and compared to demonstrate the effectiveness and benefit of the proposed model:

1) The deterministic UC without frequency constraints

In the first case, the deterministic UC is modelled without the frequency dynamic constraints. The inertia and primary frequency constraints are not considered in the model. The regulation reserve requirement is set as 1% of hourly load. The 10 minute SFR requirement, which is the sum of spinning and non-spinning reserve, is set to be greater than
the single most severe contingency. The spinning reserve requirement is at least one half of
the total SFR requirement. The 10 minute wind or load ramping event is not considered in
the deterministic model. The commitment solution for 24 hours is shown in Table 3.3
assuming all the units are on-line at initial state. The cheapest units 1, 2 and 3 are committed
for entire 24 hours; the more expensive unit 4 and 5 are OFF for the entire 24 hours.

Fig 3.1 the 5 bus test system

Table 3.1 Generator Characteristic

<table>
<thead>
<tr>
<th>Gen Name</th>
<th>Gen Bus</th>
<th>Pmin (MW)</th>
<th>Pmax (MW)</th>
<th>Energy Price ($/MW)</th>
<th>FRP Price ($/MW)</th>
<th>Ramp Rate (MW/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alta</td>
<td>A</td>
<td>40</td>
<td>40</td>
<td>14</td>
<td>12.5</td>
<td>120</td>
</tr>
<tr>
<td>Brighton</td>
<td>E</td>
<td>170</td>
<td>570</td>
<td>20</td>
<td>12.5</td>
<td>30</td>
</tr>
<tr>
<td>Park City</td>
<td>A</td>
<td>40</td>
<td>170</td>
<td>15</td>
<td>12.5</td>
<td>120</td>
</tr>
<tr>
<td>Solitude</td>
<td>C</td>
<td>100</td>
<td>520</td>
<td>30</td>
<td>12.5</td>
<td>30</td>
</tr>
<tr>
<td>Sundance</td>
<td>D</td>
<td>50</td>
<td>200</td>
<td>40</td>
<td>12.5</td>
<td>30</td>
</tr>
</tbody>
</table>
Table 3.2 Deterministic Unit Commitment Solution without Frequency Constraints

<table>
<thead>
<tr>
<th>Unit</th>
<th>Hours (1-24): $268,030</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>2</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>3</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>4</td>
<td>000000000000000000000</td>
</tr>
<tr>
<td>5</td>
<td>000000000000000000000</td>
</tr>
</tbody>
</table>

The total operation cost for 24 hours is $268,030. The dispatch solution for total regulation, spinning and non-spinning SFR is illustrated in Fig 3.2. Since the regulation reserve can be used to substitute the spinning reserve under contingency, the sum of regulation, spinning and non-spinning reserve is 40MW, which is the size of the contingency. The regulation reserve is more expensive than spinning and non-spinning, so it is procured
just to meet the hourly regulation reserve requirement. The spinning reserve is cheaper than regulation and the sum of regulation and spinning reserve is 20 MW which is half of the size of the contingency. The remaining 20 MW is procured from non-spinning reserve.

2) **The deterministic UC with frequency constraints**

In this case, the IR, PFR and SFR are all considered in the model, but the demand response and involuntary load shedding is not considered. With the frequency constraints in consideration, the unit is able to provide not only the sufficient reserve capacity, but also the inertia and ramping capability to arrest the frequency above the critical UFLS point and meet NERC DCS requirement. The unit commitment solution is shown in Table 3.3: it can be observed that the more expensive unit 4 has to be turned on for the entire 24 hours to provide the sufficient ramping capability for PFR. The total operation cost considering the frequency constraints is $304,778 which is higher than the UC solution without frequency constraints. Also, Fig 3.3 shows the dispatch solution for PFR, SFR and Regulation. The total PFR is 40 MW which is exactly the size of the most credible contingency. The non-spinning reserve is 20 MW which is half of total SFR requirement. The sum of the regulation and spinning reserve is equal to remaining half of SFR requirement.

Table 3.3 Results of Deterministic UC with Frequency Constraints

<table>
<thead>
<tr>
<th>Unit</th>
<th>Hours (1-24): $ 304,778</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1111111111111111111111</td>
</tr>
<tr>
<td>2</td>
<td>1111111111111111111111</td>
</tr>
<tr>
<td>3</td>
<td>1111111111111111111111</td>
</tr>
<tr>
<td>4</td>
<td>1111111111111111111111</td>
</tr>
<tr>
<td>5</td>
<td>0000000000000000000000</td>
</tr>
</tbody>
</table>
3) The Stochastic UC with frequency constraints

For the stochastic UC problem with generation outage contingency, two assumptions are made:

Assumption 1: the probability of two simultaneous contingency is quite low, so only single contingency event is considered in scenarios.

Assumption 2: the repair time for a generator outage is much longer than 24 hour scheduling time, so once a contingency occurs, the generator will not be available for the remainder of the hours.

In [41], the generator outage at each hour is modelled as one single scenario. The drawback of this method is that the scenario number is significantly higher since every hour is considered separately. In our stochastic model, the specific generator outage within whole 24 hours is modelled as one single scenario. Since the contingency at each hour is mutually
exclusive, the probability of contingency occurrence within 24 hours is simply the sum of probability of contingency at each hour.

In this case, the contingency events consist of the trip of unit 1 and load and wind ramping event. Assuming the MTTF of unit 1 is 500 hours, according to (3.43), the probability of unit 1 trip in each hour is 0.2%. Besides the generator outage scenario, 10 load and wind ramping events are simulated using the LHS method. So the combination of generator outage and load and wind ramping event consists of 10 scenarios in simulation. The probability of each scenario equals to $0.1\cdot0.2\%=0.02\%$. The unit commitment solution of the stochastic model is shown in Table 3.4 and the reserve dispatch solution is shown in Fig 3.4. Since the load and wind ramping scenarios are considered in the stochastic model, the spinning and non-spinning reserve are higher than the deterministic model. The regulation reserve and PFR are the same as the deterministic model. The total operation cost is $305,688 which is higher than the deterministic model.

Table 3.4 Results of Stochastic UC with Frequency Constraints

<table>
<thead>
<tr>
<th>Unit</th>
<th>Hours (1-24): $305,688</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>2</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>3</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>4</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>5</td>
<td>0000000000000000000000</td>
</tr>
</tbody>
</table>

4) The Stochastic UC with frequency constraints and demand side response

Table 3.5 Results of Stochastic UC with Frequency Constraints and Demand Response

<table>
<thead>
<tr>
<th>Unit</th>
<th>Hours (1-24): $274,389</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>111111111111111111111</td>
</tr>
<tr>
<td>2</td>
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</tr>
<tr>
<td>4</td>
<td>000000000000000000000</td>
</tr>
<tr>
<td>5</td>
<td>000000000000000000000</td>
</tr>
</tbody>
</table>
Fig 3.5 the total dispatch of reserve of Stochastic UC with frequency constraints and demand side response

Fig 3.6 the load shedding and demand response for a particular scenario

The penalty price for involuntary load shedding is set at $5,000/MW and the voluntary demand response is compensated for $50/MW. It is assumed that the involuntary load shedding can only be used in PFR stage to arrest the frequency drop and the demand
response is the slower control which can only be used in SFR stage. The UC solution of stochastic model with frequency constraints and demand side response is shown in Table 3.5. It shows that only the cheap unit 1, 2 and 3 are needed to be ON in the scheduling time and the total operation cost is only a little higher than the deterministic model without frequency constraints. Although the prices for involuntary load shedding and demand response are much higher than the reserve price from conventional unit, but they are still economical since the demand side participation avoids committing the more expensive unit. The total operation cost is $274,389 which is lower than case 2 and case 3. The dispatch for PFR and the demand side response for a particular scenario are plotted in Fig 3.5. It can be found that with demand side response, the PFR, the spinning and non-spinning SFR requirement are all 0 MW. The reason for 0 PFR and SFR requirement is that the low probability of occurrence of contingency incentivizes the operator to reduce the procurement for PFR and SFR while the reliability is barely sacrificed. The load shedding and demand response deployment for this particular scenario is shown in Fig 3.6. The expected load not served (ELNS) is 3.484 MWh which is only about 0.02% of total energy consumption.

The participation of load shedding and demand response is sensitive to the penalty price of load shedding and bidding cost for demand response. For instance, if the penalty price for involuntary load shedding increases from $5,000/MWh to $10,000/MWh, the involuntary load shedding decreases from 40 MW to 9 MW, the total PFR requirement increases from 0 MW to 31 MW and total operation cost increases to $280,694.
5) the comparison of frequency performance with and without frequency constraints

The frequency dynamic after the generator outage is simulated in Matlab/Simulink to demonstrate the improvement of frequency performance by considering the frequency dynamic constraints. The first order simplified governor-turbine model is illustrated in Fig 3.7 to approximate the dynamic frequency response of the whole system. The governor time constant is set at 0.08 s and turbine time constant is set at 0.4 s. The rate limit is the sum of short term ramping capability from all PFR providers. The droop characteristic R is set at 0.05 and the governor dead-band is assumed to be 0. The frequency dynamic is simulated and plotted in Fig 3.8. Several frequency metrics are proposed below to study the frequency performance [35]:

a) **Frequency Nadir**: The Frequency Nadir is the point where the frequency reaches its minimum point.

b) **Frequency Nadir Time**: Frequency Nadir Time is the time when the frequency reaches its minimum point.

c) **Nadir-based Frequency Response**: The Nadir-based Frequency Response is the size of the contingency divided by the frequency deviation at nadir. The unit is normalized to MW/0.1HZ.

d) **Initial RoCoF**: The initial RoCoF is the initial slope of frequency drop right after the generator contingency. Given the contingency size, the higher inertia, the flatter the RoCoF is.

It can be observed from Table 3.6 that with the frequency constraints in consideration, the frequency nadir is 59.86 HZ which is higher than 59.76 HZ without frequency constraints.
although both are higher than the UFLS point. In this case, without the frequency constraints, the frequency tends to oscillate and cannot reach the steady state within 20 seconds due to the insufficient inertia and ramping capability. With frequency constraints, more units are committed online, so the total inertia is higher and the initial RoCoF is smaller and the frequency is finally settled at 59.92 HZ.

![Diagram](image)

**Fig 3.7** the reheat Governor-Turbine model

![Graph](image)

**Fig 3.8** Frequency Performance based on solution with and without frequency constraints for 5 bus case
Table 3.6 Key Frequency Performance Metrics for 5 Bus System

<table>
<thead>
<tr>
<th>Metrics</th>
<th>With Constraints</th>
<th>Frequency</th>
<th>Without Constraints</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nadir (HZ)</td>
<td>59.86</td>
<td></td>
<td>59.76</td>
<td></td>
</tr>
<tr>
<td>Nadir Time (s)</td>
<td>2.35</td>
<td></td>
<td>2.45</td>
<td></td>
</tr>
<tr>
<td>Nadir-based PFR (MW/0.1HZ)</td>
<td>28.57</td>
<td></td>
<td>16.67</td>
<td></td>
</tr>
<tr>
<td>Settling Frequency (HZ)</td>
<td>59.92</td>
<td></td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>Initial RoCoF (HZ/s)</td>
<td>-0.19</td>
<td></td>
<td>-0.32</td>
<td></td>
</tr>
</tbody>
</table>

3.7.2 IEEE 118 bus system

The IEEE 118 bus system has 54 generators, 3 wind farms, 186 transmission lines and 91 loads. The peak demand is 3,946 MW at hour 19; the wind output is 20% of the hourly demand. Unit 11 and 28 are two candidate unit contingencies with size of 420 MW and 350 MW and 10 wind and load ramping scenarios are generated via LHS technique. The maximum allowable frequency deviation is set at 0.4 HZ. The Fig 3.9 shows the total operation cost of 4 different cases: deterministic model without frequency constraints, deterministic model with frequency constraints, stochastic model with frequency constraints, stochastic model with frequency constraints and demand side response. It can be found that the deterministic model without frequency constraints has the lowest operation cost, the deterministic model with frequency constraints has higher operational cost due to the additional frequency constraints and the stochastic model with frequency constraints has the highest operation cost since it consider both the frequency constraints and stochastic scenarios. While the stochastic model with frequency constraints and demand side response
has much lower cost than the stochastic model without demand side response and only a little more costly than the deterministic model due to the cost saving by using the demand side response. The comparison of frequency performance between traditional UC and UC with frequency constraints is plotted in Fig 3.10 and the key performance metrics are summarized in Table 3.7. It is shown that with the frequency constraints considered, the frequency nadir is much higher above the UFLS point and it takes less time to reach the nadir point and steady state point while without the frequency constraints, both the nadir time and settling time are longer.

![Graph showing operation cost comparison between 4 cases](image_url)

**Fig 3.9** The comparison of total operation cost between 4 cases
Table 3.7 Key Frequency Performance Metrics for 118 Bus System

<table>
<thead>
<tr>
<th>Metrics</th>
<th>With Constraints</th>
<th>Frequency</th>
<th>Without Constraints</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nadir (HZ)</td>
<td>59.73</td>
<td>59.58</td>
<td>Nadir Time (s)</td>
<td>1.83</td>
</tr>
<tr>
<td>Nadir-based PFR (MW/0.1HZ)</td>
<td>156.7</td>
<td>100.7</td>
<td>Settling Frequency (HZ)</td>
<td>59.83</td>
</tr>
<tr>
<td>Initial RoCoF (HZ/s)</td>
<td>-0.55</td>
<td>-0.59</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig 3.10 Frequency Performance based on solution with and without frequency constraints for 118 bus case

3.8 Conclusion

The stochastic Unit Commitment with inertia, primary and secondary frequency constraints provides us the better frequency performance after the generator outage. Various
frequency metrics, such as nadir frequency, nadir time, nadir-based frequency response and initial RoCoF, illustrate the benefit of using the proposed model. The stochastic unit commitment provides the reliable and secure solution in handling the stochastic equipment failure and short term load and wind ramping scenarios. The L-shape method is applied to solve the large scale stochastic problem more efficiently. The demand side response, including involuntary load shedding and voluntary demand response are modelled to participate in frequency control and provide a cost-saving solution. With the inclusion of frequency constraints and demand side response, both the economics and frequency performance can be improved. The pricing scheme and market settlement scheme will be further studied in the future research.
CHAPTER 4 ESTIMATION OF REGULATION RESERVE REQUIREMENT BASED ON CPS1

4.1 Introduction

The load frequency control (LFC) is designed to correct the moment to moment generation-load imbalance so that the frequency is maintained close to the nominal value (60 Hz in North America) and the tie-line flow is maintained within a narrow dead-band around the scheduled interchange [28]. To the extent that wind and solar displace conventional generation; increasing their penetration will adversely affect frequency control performance since wind and solar increase MW variability. As a consequence, the control performance is expected to degrade as the renewable penetration increases [27], unless mitigating actions are taken.

The short term forecast of control performance is useful in maintaining power system reliability, and has been explored previously. For example, in [42], the Artificial Neural Network (ANN) is applied to forecast the short term Area Control Error (ACE), and in [43], a method is proposed to estimate CPS1 using the probability distribution of area load change. Our objective in this work is to provide real-time estimation of regulating reserve requirements based on target CPS1. We approach this problem by employing the Multiple Linear Regression (MLR) model, to estimate the relationship between CPS1 and the predictors on which CPS1 depends, e.g., load variability; wind variability; regulation reserve requirement; load forecast level; wind forecast level and hour of the day. The proposed MLR model can then be used to estimate the regulation reserve requirement based on the forecast of the other predictors and target CPS1 requirement. The main advantage of MLR comparing
to other predicting model lies in its interpretability, simplicity, transparency and most importantly, its ability to derive the real time regulation reserve requirement from the MLR model which is the major contribution of the proposed method.

The MLR has been applied in several areas of power system engineering. For example, the MLR is used in [44]-[45] to extract the relationship between the damping of electromechanical modes and system operating condition. Bruno et al. used the MLR to predict the voltage stability margin (VSM) from the reactive power reserve (RPR) in an online environment [46]. Also several researches applied the MRL in short-term load forecasting [47]-[48].

There are also numerous papers that have been published for determining the regulation reserve requirement with high renewable penetration. The literature reviews are presented in section 1.2. The contribution of this chapter is to develop the MLR model to predict the CPS1 in short term and use the model to estimate the regulation reserve requirement for meeting the NERC control standard.

4.2 Low Order LFC Model

The LFC is the feedback control system consisting of two control loops: the primary control loop and the supplementary control loop. The primary control loop uses the governor droop characteristic to arrest the frequency drop and restore the frequency back to the steady state after the contingency. The supplementary control loop is also called Secondary Frequency Control (SFC) or Automatic Generation Control (AGC). It utilizes a proportional-integral (PI) controller to achieve the following two main objectives [2]:
1) Maintain the frequency close to the nominal value.

2) Maintain the tie line flow close to the scheduled interchange between control areas.

The block diagram of the LFC is illustrated in Fig 4.1 in which $\Delta f$ is the frequency deviation, $\Delta P_l$ is the net load deviation, $M$ is the inertial constant, $D$ is the load damping coefficient, $R$ is the governor droop characteristic, $\beta$ is the frequency bias factor, $K_P$ and $K_I$ are the AGC controller gains, $T_G$ is the governor time constant and $T_T$ is the turbine time constant.

Fig 4.1 Low order LFC model

The parameters of the LFC model can be tuned by the real system observations or obtained from the classical low order LFC model [49]. The blocks for Ramp Rate Limiter and Capacity Limiter are two important nonlinearities in the low order LFC model. The Ramp Rate Limiter reflects the ramping capability of the regulation unit fleet, and it restricts the ramp rate of the regulation unit output. The ramping capability of the regulation unit largely depends on its generator type which can range from less than 10% of its rating per minute for coal and oil units to more than 100% of its rating per minute for flywheels and batteries [50]. The Capacity Limiter restricts the maximum upward and downward deviation
from the base-load point; it is determined by the market scheduling processes Unit Commitment (UC) or Economic Dispatch (ED).

The focus of this chapter is on the adequacy of the regulation reserve in response to normal net load variation. Therefore, we neglect representation of the primary frequency control, under the assumption that corresponding frequency variations are within the dead band of the primary controller, assumed to be 0.036 HZ [51].

4.3 NERC Control Performance Standard

The CPS1 and CPS2 were adopted by NERC in 1997; they are aimed to measure the performance of each control area to control the frequency deviation and the interchange flow within a specific bandwidth about the nominal value [52]. The new control performance metric BAAL is proposed by NERC to replace CPS2, and it is currently undergoing field trials [52].

1. CPS1& CPS2

CPS1 is the 12 month rolling average control performance metric. It is expressed as follows [53]:

\[
CPS1 = (2 - CF1) \times 100\%
\]

\[
CF1 = \frac{(CF_{1_{\text{min}}}^{1_{\text{12month}}})^2}{(\varepsilon_1)^2}
\]

\[
CF_{1_{\text{min}}} = \frac{ACE_{1_{\text{min}}} \times \Delta f_{1_{\text{min}}}}{-10B}
\]
where B is the control area frequency bias in MW/0.1 Hz. The control area should set -10B as close as possible to the control area frequency response factor $\beta$. The minimum requirement for B is at least 1% of its estimated maximum generation level in next year per 0.1 Hz change [54]. $\Delta f_{1\text{min}}$ is the 1 minute average of frequency deviation. $ACE_{1\text{min}}$ is the 1 minute average of ACE. $\varepsilon_1$ is the specified steady state frequency bound for each interconnection. It is 0.018 Hz in Eastern Interconnection (EI), 0.0228 Hz in Western Interconnection (WI) and 0.03 Hz in ERCOT [55]. The minimum score for CPS1 is 100%. If the CPS1 is greater than 100%, the control area is helping the interconnection frequency response (either over-generating during under-frequency condition or under-generating during over-frequency condition); otherwise the control area is hurting the interconnection frequency response (either under-generating during under-frequency condition or over-generating during over-frequency condition).

CPS2 is designed to limit the unscheduled tie line flow by requiring the absolute value of 10 minute average ACE to remain within the predefined limit (L10) more than 90% of time in one month, expressed as [56]:

$$CPS2 = 100 \left( 1 - \frac{\text{Num}(\{ ACE_{10\text{min}} \geq L_{10} \})}{\text{Num}(10 \text{ min intervals})} \right) \%$$

(4.4)

$$L_{10} = 1.65 \varepsilon_{10} \sqrt{(10B_i)(10B_s)}$$

(4.5)

where $\varepsilon_{10}$ is the root mean square of the 10 minute frequency average over a given year for the interconnection. $B_i$ is the frequency bias for the balancing authority and $B_s$ is the sum of
the frequency bias over the whole interconnection. CPS2 will be replaced by BAAL due to the following issues [54]:

1) CPS2 does not have the frequency component.
2) CPS2 only requires 90% of compliance.
3) CPS2 may cause the control to degrade frequency performance.

2. BAAL

The goal of BAAL is to maintain the interconnection frequency within predefined Frequency Trigger Limit (FTL). The upper and lower bound of FTL is determined by the under frequency load shedding (UFLS) threshold and turbine over-speed relay. The formulation of BAAL can be expressed as follows [55]:

when \( f_a < f_s \),

\[
BAAL_{low} = \left( -10B_i \times (FTL_{low} - f_s) \right) \times \frac{FTL_{low} - f_s}{f_a - f_s}
\] (4.6)

when \( f_a > f_s \),

\[
BAAL_{high} = \left( -10B_i \times (FTL_{high} - f_s) \right) \times \frac{FTL_{high} - f_s}{f_a - f_s}
\] (4.7)

where \( BAAL_{low} \) is the lower bound for BAAL, \( BAAL_{high} \) is the upper bound for BAAL, \( B_i \) is the balancing authority frequency bias setting, \( f_a \) is the actual frequency measurement, \( f_s \) is the scheduled frequency, \( FTL_{high} \) is the high frequency trigger limit and \( FTL_{low} \) is the low frequency trigger limit. They can be calculated as (4.8)-(4.9) where \( \varepsilon_1 \) is the same as which is used in CPS1:

\[
FTL_{low} = f_s - 3\varepsilon_1
\] (4.8)
\[ FTL_{\text{high}} = f_x + 3\epsilon_i \]  

The BAAL requires each BA to keep the generation and load in balance so that the clock minute average ACE will not exceed the BAAL bound for 30 consecutive minutes.

Since both CPS2 and BAAL counts the number of violations for which the ACE signal violates the L10 limit or BAAL limit, respectively, their relationship with regulation reserve requirement follow a non-continuous function. So in this chapter we only use CPS1 to estimate the regulation reserve requirement.

### 4.4 Data Preparation

Wind and load data for 31 winter days are obtained from the CAISO operating region at 1 minute resolution [57]. The wind penetration is 13% which is estimated as the ratio between the maximum wind MW output and peak load from the sample data. The net load is calculated as load net of wind, and the spline interpolation is used to generate net load data at 1 second resolution. The regulation reserve for 31 winter days is randomly generated from a uniform distribution between 150 and 300 MW which coincides with the regulation reserve range based on PJM practice shown in the introduction chapter Table 1.1. Since the actual desired dispatch point (DDP) data is not available for public access, the 5 minute average of actual net load plus certain wind and load forecast error is used as the real time DDP. The standard deviation of 5 minute load forecast error is approximated to be 0.5% of the hourly load level, and the standard deviation of 5 minute wind forecast error is approximated to be 1% of the hourly wind level. The Latin Hypercube Sampling (LHS) is used to randomly generate the wind and load forecast errors following the normal distribution with 0 mean and standard
deviation specified as indicated above. The difference between the actual net load curve and the DDP curve is referred to as the net load deviation; it is covered by the procured regulation reserve. The real time market control process is illustrated in Fig 4.2.

The parameters of the LFC system are taken from the classical model; they are summarized in Table 2 [49]. The net load deviation is fed into the LFC system as the input and the outputs are $\Delta f$ and ACE. The NERC compliance for CPS1 is based on the 12 month rolling average of $CF_{1\text{min}}$. Since the focus of this model is on short term CPS1 prediction and short term regulation reserve requirement estimation, the hourly average $\left(CF_{1\text{min}}\right)_{\text{hour}}$ is used to replace the NERC 12 month rolling average $\left(CF_{1\text{min}}\right)_{\text{12month}}$ in (4.2). This is justified because: 1), the hourly CPS1 compliance guarantees the NERC 12 month CPS1 compliance; 2) the hourly CPS1 score reflects the system short-term control performance; 3), the system operator procures the majority of regulation reserve from the hourly market. The predictors directly related to the CPS1 includes load variability; wind variability; regulation reserve requirement; load forecast level; wind forecast level and hour of the day. Among these predictors, the regulation reserve requirement is determined from UC or ED and it is controllable while the other load/wind conditions are normally not controllable assuming the demand side resource is not considered in the scope of this chapter. It is also possible to include the weekday/weekend, month and season information in predicting the CPS1. Since those information will highly impact the regulation reserve requirement in a longer time frame and they could be easily included in the model as the sufficient long term data is provided.
Fig 4.2 Illustration of the CAISO control process

Table 4.1 Parameter of Lower Order LFC model

<table>
<thead>
<tr>
<th>( K_P )</th>
<th>( K_I )</th>
<th>( T_G )</th>
<th>( T_R )</th>
<th>( M )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>0.03</td>
<td>0.08</td>
<td>0.4</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( D )</th>
<th>( R )</th>
<th>( \beta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.05</td>
<td>21</td>
</tr>
</tbody>
</table>

4.5 Model Building Process

The process of building the MLR model is illustrated in Fig 4.3. The process includes three steps: feature selection, coefficient estimation and model validation. Each of these steps will be explained and illustrated in the following sub-sections.
Based on the engineering knowledge and experience, 28 variables are first selected as the candidates for feature selection which includes 23 qualitative variables and 5 quantitative variables as shown in Table 4.2. Since CF1 is a simple linear function of CPS1 as shown in formulation (4.1), we use the CF1 as the response variable in the remainder of the chapter and the logarithm transformation is used to convert CF1 to log(CF1) for achieving the constant variance of residual. The detail of the transformation will be presented in section 4.5.3. The 23 qualitative variables represent 23 hours while the hour 1 is set as the reference. The 5 quantitative variables include: load variability; wind variability; regulation reserve capacity; load forecast level and wind forecast level. The linear term, quadratic term and
interaction term of these 28 variables comprise totally 159 predictors. With the quadratic and interaction terms included in the model, the complexity of the model will increase significantly and it may result in over-fitting. The feature selection technique is used to reduce the complexity of the model while achieving a balance between bias and variance. The variance refers to the variance of the prediction in using the model for different sets of test data; the bias refers to the error introduced by the model to abstract the true relationships. The goal of the feature selection is to select the variables that achieve low bias and low variance simultaneously.

Among the numerous techniques of feature selection, the stepwise selection is one of the most effective methods to achieve both the high computational efficiency and low model variance. The stepwise selection method includes the exhaustive search, forward selection method, backward selection method and hybrid selection method. The exhaustive search will fit a separate linear regression model for each possible combination of P predictors. The disadvantage of the exhaustive method is that it is computationally expensive when P is very large and so it is not considered here. The forward selection method adds one best predictor into the model at each step. The backward selection method starts with all predictors and deletes the least useful predictor one-at-a-time. The hybrid selection model implements the forward selection and backward selection sequentially. We have found through testing the forward selection method performs best, as is described below.
Table 4.2 Definition of the variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition of the variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y$</td>
<td>Log(CF1)</td>
</tr>
<tr>
<td>$x_{1-23}$</td>
<td>Hour of day</td>
</tr>
<tr>
<td>$x_{24}$</td>
<td>Load variability</td>
</tr>
<tr>
<td>$x_{25}$</td>
<td>Wind variability</td>
</tr>
<tr>
<td>$x_{26}$</td>
<td>Regulation reserve requirement</td>
</tr>
<tr>
<td>$x_{27}$</td>
<td>Load forecast</td>
</tr>
<tr>
<td>$x_{28}$</td>
<td>Wind forecast</td>
</tr>
</tbody>
</table>

The algorithm of the forward stepwise selection is as follows [28]:

**Algorithm: Forward Stepwise Selection**

**Step1**: Denote the $M_P$ as the null model which includes no predictors.

**Step2**:

For $k = 0, \ldots, P-1$, Do:

1) Consider all the possible $p-k$ models which add one additional predictor into the model $M_k$.

2) Select the best one from the $p-k$ models based on the minimum Mean Squared Error (MSE) as expressed in (4.10) where $y_r$ is the measured response, $\hat{y}_r$ is the prediction response, and $N$ is the number of samples:

$$MSE = \frac{1}{N} \sum_{r=1}^{N} (y_r - \hat{y}_r)^2 \quad (4.10)$$
**Step3**: Select the best model from the models $M_0$, $M_1$, … , $M_p$ based on the minimum Cross Validation (CV) prediction error.

In this chapter, the 10-fold CV is used to select the best model from the candidate model $M_0$, $M_1$, … , $M_p$. The 10-fold CV randomly divides the data set into 10 groups of approximately equal size. One group is used as the test data set to calculate the test error and the remaining 9 groups are used to fit the model. This process is repeated 10 times for each model $M_0$, $M_1$, … , $M_p$. The resulting test error is stored in a $10 \times p$ matrix in which each row represents one of the 10 different CV group and each column represents one of the $p$ different models. The average CV prediction error for each model $M_k$ is computed in (4.11):

$$CV_k = \frac{1}{10} \sum_{i=1}^{10} MSE_{i,k}$$  \hspace{1cm} (4.11)

Fig 4.4 shows the mean CV error with model predictors for three feature selection methods. It is observed that the forward selection method (green dotted line) gives the lowest CV prediction error and lowest prediction error volatility among the three methods so the forward selection is used to select the most relevant predictors.
Fig 4.4 Mean CV error vs. Number of predictors

Fig 4.4 also illustrates the relationship between the mean CV prediction error and the number of the predictors. The plot shows the model with 26 predictors results in the best compromise between the prediction error and model complexity. The model prediction error even increases a little bit with more than 26 predictors due to the over-fitting. After the feature selection, the 26 most relevant predictors are selected and the coefficient of each predictor is estimated, as is described in the next subsection.

4.5.2 Coefficient Estimation

The MLR can be expressed as the formulation (4.12) which includes the linear term, quadratic term and interaction term [58]. The interaction term here represents the product between two variables.

\[
y_i = \beta_0 + \sum_{i=1}^{p} \beta_i x_{i,j} + \sum_{i=1}^{p} \beta_i x_{i,j}^2 + \sum_{i=1}^{L} \gamma_i x_{ij} + u_i
\]  

(4.12)
In (4.12), $\beta_0$ is the intercept, $\beta_i$ is the coefficient for the linear term, $\beta_{ii}$ is the coefficient for the quadratic term, $\gamma_i$ is the coefficient for the interaction term and $\epsilon_i$ is the error term which follows the normal distribution with zero mean and constant variance, written as $\epsilon_i \sim N(0, \sigma^2)$. Although the model includes the high order term for the predictors, the coefficient for each term is still linear so they can be solved by the ordinary least square (OLS) method [59]. The OLS is an unconstrained optimization problem to minimize the residual sum of squares (RSS) and it can be written in compact vector-matrix form (4.13) as:

$$\hat{\beta} = \arg \min \beta (y - X\beta)^T (y - X\beta)$$

(4.13)

where $X \in N \times (P + 1)$ is the sample predictor matrix with 1 in the first column, $y \in N \times 1$ is the sample response vector, $\beta \in P \times 1$ is the coefficient vector, $N$ is the number of samples and $P$ is the number of predictors. Differentiating the objective function with respect to coefficient vector $\beta$ and equating the derivative to zero provides us the solution in the form of (4.14). The estimated coefficient of each selected predictor is illustrated in Table 4.3.

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

(4.14)
Table 4.3 Summary of MLR output

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-1.22e-0</td>
</tr>
<tr>
<td>H4</td>
<td>-6.41e-1</td>
</tr>
<tr>
<td>H10</td>
<td>-8.44e-1</td>
</tr>
<tr>
<td>H20</td>
<td>-2.48e-1</td>
</tr>
<tr>
<td>LV</td>
<td>7.95e-2</td>
</tr>
<tr>
<td>WV</td>
<td>4.63e-2</td>
</tr>
<tr>
<td>LV^2</td>
<td>-2.16e-4</td>
</tr>
<tr>
<td>WV^2</td>
<td>-1.58e-4</td>
</tr>
<tr>
<td>REG^2</td>
<td>-3.86e-5</td>
</tr>
<tr>
<td>H4:LV</td>
<td>4.20e-2</td>
</tr>
<tr>
<td>H10:LV</td>
<td>3.50e-2</td>
</tr>
<tr>
<td>H11:LV</td>
<td>1.06e-2</td>
</tr>
<tr>
<td>H24:LV</td>
<td>-6.89e-3</td>
</tr>
<tr>
<td>H7:WV</td>
<td>8.63e-3</td>
</tr>
<tr>
<td>H16:WV</td>
<td>4.67e-3</td>
</tr>
<tr>
<td>H18:WV</td>
<td>-3.76e-2</td>
</tr>
<tr>
<td>H5:REG</td>
<td>1.22e-3</td>
</tr>
<tr>
<td>H18:REG</td>
<td>4.33e-3</td>
</tr>
<tr>
<td>H21:REG</td>
<td>5.33e-3</td>
</tr>
<tr>
<td>H8:LF</td>
<td>3.25e-5</td>
</tr>
<tr>
<td>H21:LF</td>
<td>-4.17e-5</td>
</tr>
<tr>
<td>H22:LF</td>
<td>-1.82e-5</td>
</tr>
<tr>
<td>H8:WF</td>
<td>-1.14e-4</td>
</tr>
<tr>
<td>H23:WF</td>
<td>-4.34e-5</td>
</tr>
<tr>
<td>LV:WV</td>
<td>-3.70e-4</td>
</tr>
<tr>
<td>WV:REG</td>
<td>1.23e-4</td>
</tr>
<tr>
<td>REG:LF</td>
<td>9.34e-8</td>
</tr>
<tr>
<td>R^2</td>
<td>0.84</td>
</tr>
<tr>
<td>F-statistics</td>
<td>20</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt; 2.2e-16</td>
</tr>
</tbody>
</table>

Table 4.4 shows the statistical metrics for the MLR model. The residual standard error (RSE) is the estimate of the standard deviation of residual. The metric R^2 measures the contribution of the fitted model to the total variance of the response. In our simulation, R^2=0.84 means 84% of the variance in the original response data sets can be explained by the fitted MLR model. Both the F-statistics and p-value provides strong evidence that the predictors are closely related to the response.

Table 4.4 Statistical Metrics for MLR

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residual Standard Error</td>
<td>0.64</td>
</tr>
<tr>
<td>R^2</td>
<td>0.84</td>
</tr>
<tr>
<td>F-statistics</td>
<td>20</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt; 2.2e-16</td>
</tr>
</tbody>
</table>

4.5.3 Model Validation

After fitting the MLR model, a model validation process is performed to check the constant variance of residual and the correlation of residual [58].
1) Constant Variance of Residual

The standard error (SE) for parameters, the hypothetical test, and the confidence interval are all based on the assumption that the residual has constant variance. However, in many cases, this assumption may not be true. This phenomenon is also called heteroscedasticity [59]. Fig 4.5 shows the residual versus CF1 without transformation. It is shown that the residual is not normally distributed and the variance of residual is not constant. The way to resolve this problem is to transform the response CF1 using the Box-Cox Power Transformation [60]. Fig 4.6 shows the residual versus log(CF1) after the logarithm transformation. It can be observed that the variance of the residual is much closer to being normal and constant; this provides that the statistical analysis is more accurate after the logarithm transformation.

![Fig 4.5 Residual vs. CF1](image)

Fig 4.5 Residual vs. CF1
2) The Correlation of Residual

Another important assumption is that the time series terms of the residual should be uncorrelated. The correlation between the residuals will tend to underestimate the RSE so that the confidence interval (CI) and prediction interval (PI) can be underestimated. Fig 4.7 shows the autocorrelation function (ACF) plot of the error term. It is observed that the error term has very little correlation with the error term at time t-k, k=1, 2, 3…, so the effect of serial correlation can be neglected.
4.6 Application of the MLR Model

The MLR model is aimed to abstract the potential relationship between the various predictors and CPS1 score. The application of the proposed model can be used to estimate the short term regulation reserve requirement.

The application is based on the observation that given the relationship between CPS1 and various predictors (obtained via MLR approach), it is easy to derive the minimum requirement of regulation reserve to satisfy the target CPS1 score with the other predictors forecasted. In our model, the load and wind variability, load and wind output level are predictors that cannot be controlled by the operator, while the regulation reserve capacity is controllable from the market scheduling process. So given the forecast of load and wind condition, the regulation reserve requirement can be derived from (4.12) by substituting the forecasted predictor value, and it can be expressed as the quadratic function of regulation reserve capacity, as in (4.15).
\[
\alpha_0 + \alpha_1 \text{REG} + \alpha_2 \text{REG}^2 \leq \log(\text{CF1}_{\text{tar}})
\]  
(4.15)

Here REG is the regulation reserve requirement and CF1_{\text{tar}} is the target CF1 score, \(\alpha_0\), \(\alpha_1\) and \(\alpha_2\) are the coefficients of the quadratic function after substituting other given predictors into (4.12). By solving the quadratic equation, the minimum regulation reserve requirement is obtained on an hourly basis. The regulation reserve requirement is then sent into the market dispatch process to procure the regulation reserve. The selected regulation units will provide the secondary frequency response service in the LFC process. The ACE output from the LFC process is used to calculate the hourly CPS1 score; the new CPS1 score is sent to the historical database for updating the MLR model. The flowchart of the integrated UC-LFC and regulation estimator is illustrated in Fig 4.8.

![Flowchart of integrated LFC and regulation estimator](image)

We have used a multiple linear regression model.

For CF1 outside of 0.6 \leq \text{CF1} \leq 1.0, compute RegReserves to achieve CF1=0.8.

Forecasted values of

- Load MW level
- Wind, solar MW level
- Load variability
- Wind, solar variability
- Portfolio ramping
- Errors

The proposed model can be used in the online environment in which the new data set is collected and the model is updated rapidly. The recursive least square (RLS) provides an efficient way to update model parameters from the old one to the updated new one to
accommodate the new data set [61]. RLS uses the old model parameters and new data sets to calculate the new model parameters. The generalized expression for the RLS is shown as (4.16) and (4.17):

\[ G_1 = G_0 + X_1^T X_1 \]  
\[ \beta_1 = \beta_0 + G_1^{-1} X_1^T (y_1 - X_1 \beta_0) \]

where \((X_1, y_1)\) is the new data set, \(\beta_0\) is the old model parameter, \(\beta_1\) is the new model parameter and \(G_0 = X_0^T X_0\). In (4.15), the target CF1 score is dynamically adjusted based on the 24 hour moving average CF1 score. The reason for choosing 24 hour moving average CF1 score is based on the consideration that: 1), it can be used to determine the real time regulation reserve requirement while the NERC 12 month moving average CF1 is a long term metric, 2), it can reduce the volatility of CF1 score comparing to the shorter term CF1 moving average, e.g., one hour or 5 minute, 3), the 24 hour CF1 moving average is more restrictive than NERC requirement so it ensure the compliance with NERC requirement. The integrated model shown in Fig 4.8 is tested on one day of data representing the CAISO system; the low order LFC model shown in Fig 4.1 is simulated to provide observations of the CF1 performance. The regulation reserve requirement and frequency performance CF1 score based on the proposed method is compared to those obtained from use of the PJM method and from use of the NREL method. The PJM method is described in , and the NREL method is computed according to (4.18) where \(\sigma_{xt}\) (Hourly Wind) is the standard deviation of wind forecast uncertainty, and REG is the regulation reserve requirement [33]:
\[ REG \geq 3 \sqrt{\left(\frac{0.01 \cdot \text{Hourly Load}}{3}\right)^2 + \sigma_{ST}^2 \cdot (\text{Hourly Wind})^2} \quad (4.18) \]

Fig 4.9 shows the regulation reserve requirement based on PJM method, NREL method and the proposed CPS1 based method. Fig 4.10 shows the CF1 score obtained for the three methods over a 24 hour period. It is observed from Fig 4.10 that at hours 5, 17 and 18, CF1 spikes much higher than 1.0 (NERC CPS1 requirement) based on the PJM and NREL methods. The CF1 spikes indicate the net load variability is greater than at other hours, and the regulation reserve is insufficient to maintain the satisfactory CF1 score. With the proposed CPS1 based method, the regulation reserve requirement in hours 5, 17 and 18 is adjusted upward accordingly so that the CF1 score for these hours are much lower than those of the other two methods. It can also be observed that during some other hours, the proposed method requires less regulation reserve than that of the PJM method or the NREL method. This is because in these hours, the net load is less variable and the regulation reserve requirement from the CPS1-based method is lower than at other hours. The PJM method and NREL method are not able to capture the dynamic nature of the net load condition and may over-procure the regulation reserve and incur the higher procurement cost, or they may under-procure the regulation reserve and incur lower control performance. It is shown in Table 4.5 that both average CF1 score and CF1 standard deviation are lower with the proposed CPS1-based method while the total regulation requirement cost is still lower than it is with the other two methods.

The comparison of these three methods is also implemented for a higher wind penetration level. Fig 4.11 and Fig 4.12 show the regulation requirement and the CF1 score for a 24 hour
period under a 30% wind penetration. As the wind penetration increases, the regulation reserve requirement also increases significantly. With the proposed CPS1-based method, the CF1 score is controlled very well around 1.0 and the CF1 variance is lower than other two methods. In this scenario, the PJM method and NREL method tend to under-procure the regulation reserve to meet the NERC CPS1 requirement.

![Graph showing regulation requirement between different models under 13% wind penetration](image)

**Fig 4.9 Regulation Requirement between different models under 13% wind penetration**

The regulation reserve is required to be able to deploy in 5 minutes. So the minimum ramp rate of the regulation unit fleet should be no less than 20% of regulation capacity per minute. The actual regulation ramping capability is dependent on the generation mix of units providing regulation. As the proportion of fast ramping units in the generation mix increases, the regulation capacity requirement can be reduced and the procurement cost can also be reduced. Fig 4.13 shows the 24 hour regulation reserve requirement with different ramping capability scenarios at 20%, 40% and 60% of regulation capacity per minute. The target
CPS1 score is set at 100% for three scenarios and it is observed that the regulation reserve requirement is reduced as the ramping capability increases. There are numerous emerging technologies that can provide the high quality regulation reserve to increase the ramp rate of regulation reserve, e.g., flywheel, battery, compressed air energy storage (CAES), demand side response, plug-in vehicle and even wind and solar control. The Federal Energy Regulatory Commission (FERC) also issued Order 755 to encourage fast ramping units to provide regulation reserve and receive associated compensation [31]. As the penetration of wind and solar increases, sufficient ramping capability from the emerging technologies will be required to satisfy the NERC control performance standard while keeping the regulation capacity requirement low.

Fig 4.10 CF1 score between different models under 13% wind penetration
Table 4.5 Comparison of cost and performance between three methods under 13% wind penetration

<table>
<thead>
<tr>
<th>Method</th>
<th>Total 24h Procurement (MW)</th>
<th>Total 24h Procurement Cost ($)</th>
<th>24h CF1 Average</th>
<th>24h CF1 Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PJM</td>
<td>7,569</td>
<td>44,345</td>
<td>1.27</td>
<td>2.36</td>
</tr>
<tr>
<td>NREL</td>
<td>6,984</td>
<td>40,114</td>
<td>1.53</td>
<td>2.73</td>
</tr>
<tr>
<td>CPS1 based</td>
<td>5,992</td>
<td>30,919</td>
<td>0.87</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Fig 4.11 Regulation Requirement between different models under 30% wind penetration
Fig 4.12 CF1 score between different models under 30% wind penetration

Table 4.6 Comparison of cost and performance between three methods under 30% wind penetration

<table>
<thead>
<tr>
<th>Method</th>
<th>Total 24h Procurement (MW)</th>
<th>Total 24h Procurement Cost ($)</th>
<th>24h CF1 Average</th>
<th>24h CF1 Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PJM</td>
<td>7,569</td>
<td>44,345</td>
<td>1.75</td>
<td>2.56</td>
</tr>
<tr>
<td>NREL</td>
<td>8,546</td>
<td>48,373</td>
<td>0.82</td>
<td>1.28</td>
</tr>
<tr>
<td>CPS1 based</td>
<td>7,352</td>
<td>39,017</td>
<td>1.09</td>
<td>0.93</td>
</tr>
</tbody>
</table>
Fig 4.13 Regulation Requirement under different ramp rate

4.7 Conclusion

This chapter uses MLR to abstract the relationship between NERC standard CPS1 and the predictors including the hour of day, load and wind condition and regulation reserve requirement. The model training data is generated from the classical low order LFC model. The data transformation and validation ensure the validity of the proposed model. The forward stepwise method with cross validation is used to select the most relevant predictors and make the tradeoff between model bias and model variance. The statistical metrics illustrate that the model can predict CPS1 accurately and effectively with given forecast of predictors.

The proposed model can be applied in power system operation to estimate the regulation reserve requirement and instruct the system operator to procure sufficient regulation reserve to satisfy NERC CPS1 requirement while maintain the economic efficiency. The simulation
result shows the proposed CPS1 based regulation reserve requirement provides for satisfactory CPS1 performance while maintaining a low total procurement cost of regulation capacity. The model is also tested in a high wind penetration scenario (30%), where simulation results show promising CPS1 performance compared to that of other regulation procurement methods.

The recursive least square (RLS) method enables the model to be updated in online environment when new data is available. The target CPS1 score is also dynamically adjusted based on the 24 hour moving average CPS1 score.

The observations for training the model are obtained from the simplified LFC simulation so that some factors are not considered. For instance, the unit uninstructed deviation is an important factor influences the system control performance while in the simulation the generation output is assumed to perfectly follow the AGC signal. Because of the limitation of data availability, these types of information are not available for the model, but they are critical in real system CPS1 performance and should be studied in the future research.
CHAPTER 5 STOCHASTIC ECONOMIC DISPATCH WITH FLEXIBLE RAMPING PRODUCT

5.1 Introduction

The increasing penetration of wind and solar imposes the more serious challenge to the power system operation. Due to the uncertainty and variability of wind and solar, the real time system operation requires more flexible ramping capability than before. Midcontinent ISO and California ISO are proposing to implement the flexible ramping constraints or flexible ramping product to address this operational challenge. Without the sufficient ramping capability, the real time market may not be able to follow the net load condition from one dispatch point to the next. The consequence of the insufficient ramping capability may be multiple. From the economic aspect, it may trigger the real time market price spike caused by the constraint violation penalty price and it may distort the market efficiency and send the wrong price signal to market participants. From the reliability aspect, the insufficiency of the ramping capability may deteriorate the system control performance such as Control Performance Standard 1 (CPS1) and Balancing Authority ACE Limit (BAAL) and may even cause the system instability or cascading blackout.

In this chapter, a stochastic economic dispatch with flexible ramping product is developed and the transmission constraint is included to guarantee the deliverability. The advantage of the proposed model is threefold: first, it is robust and secure against the most extreme scenarios from uncertainty. Second, only a limited number of scenarios are required and it is computational tractable. Third, the bus level uncertainty enables us to model the impact of transmission restriction on the flexible ramping product.
5.2 Model Formulation

In this section, the system-wise flexible ramping product model is proposed first, and then the zonal flexible ramping product model is proposed secondly to account the product deliverability for transmission congested zone. Lastly a stochastic model with nodal flexible ramping product will be proposed and the benefit of the stochastic model will be illustrated in subsequent case study. All the model formulations are based on the California ISO market design of flexible ramping product [20]. For simplicity, only the energy and the flexible ramping product are considered in the formulation, it can be extended to other ancillary service without loss of generality. The look ahead economic dispatch may consider the system condition for multiple intervals and pre-position some generators to prepare for the possible future ramping scenario. The first interval is called the binding interval which assumes the forecast are accurate and both dispatch and price are binding. The net load deviation from the forecast will be covered by the regulation reserve. The rest of intervals are called the look-ahead interval in which price and dispatch are all advisory and may be updated while it becomes the binding interval. The requirement of the flexible ramp product is illustrated in Fig 5.1 [20].
Fig 5.1 Illustration of ramping capability requirement

The nomenclature for the following sub-section is listed as follows:

\( C() \) The cost function for different types of market product

\( g(i, t) \) The energy dispatch at bus \( i \), interval \( t \)

\( FRU(i, t) \) The flexible ramp up (FRU) product at bus \( i \), interval \( t \)

\( FRD(i, t) \) The flexible ramp down (FRD) product at bus \( i \), interval \( t \)

\( g(i, t+1, s) \) The energy dispatch at bus \( i \), interval \( t+1 \) and scenario \( s \)

\( SF_{li} \) Shift factor of the bus \( i \) over line \( l \)

\( d(i, t) \) The net load (Load-Wind) at bus \( i \), interval \( t \)

\( d(i, t+1, s) \) The net load at bus \( i \), interval \( t+1 \) and scenario \( s \)
The maximum power flow limit at line $l$ is denoted by $fl_{max}(l)$. The ramp rate of unit at bus $i$ in MW/min is denoted by $RR(i)$. The generator maximum capacity at bus $i$ is denoted by $P_{max}(i)$. The generator minimum capacity at bus $i$ is denoted by $P_{min}(i)$.

### 5.2.1 Economic Dispatch with system-wise flexible ramping requirement

The objective function (5.1) is to co-optimize the bid cost for energy and flexible ramping product. The constraints include the power balance constraint (5.2), power flow constraint (5.3), maximum Flexible Ramping Product capacity limit constraints (5.4)-(5.5), generator capacity limit constraint (5.6)-(5.7) and system wise flexible ramping product requirement constraint (5.8)-(5.9). The Market Clearing Price for Flexible Ramping Product is the Lagrangian variable corresponds to the system wise flexible ramping product requirement constraint and the price is unique for the whole system.

Minimize

$$\sum_{i} C(g(i,t)) + C(FRU(i,t)) + C(FRD(i,t))$$

(5.1)

$$\sum_{i} g(i,t) = \sum_{i} d(i,t) \quad \forall t$$

(5.2)

$$\sum_{i} SF_{l}(g(i,t) - d(i,t)) \leq fl_{max}(l) \quad \forall l, t$$

(5.3)

$$FRU(i,t) \leq 5 \cdot RR(i) \quad \forall i, t$$

(5.4)

$$FRD(i,t) \leq 5 \cdot RR(i) \quad \forall i, t$$

(5.5)

$$g(i,t) + FRU(i,t) \leq P_{max}(i) \quad \forall i, t$$

(5.6)
\[ g(i,t) - FRD(i,t) \geq P_{\text{min}}(i) \quad \forall i, t \quad (5.7) \]
\[ \sum_i FRU(i,t) \geq FRU_{\text{req}}(t) \quad \forall t \quad (5.8) \]
\[ \sum_i FRD(i,t) \geq FRD_{\text{req}}(t) \quad \forall t \quad (5.9) \]

5.2.2 Economic Dispatch with zonal flexible ramping requirement

The objective function and most of the constraints in this section are the same as the ones in last section. The only difference is that with the zonal flexible ramping product, the flexible ramping product is not only required to meet the system requirement, but also the zonal requirement for certain transmission restrictive zone. The constraints (5.10)-(5.11) represent the flexible ramping requirement for transmission restrictive zone Z. The excessive flexible ramping product in zone Z can be used to meet the larger zone requirement or whole system requirement. The MCP for flexible ramping product is no longer the unique one in whole system. The price cascading effect decides that the MCP in bottom level zone is larger than the one in the upper level zone. For instance, there are two zone in the control area, zone Z1 and zone Z2. Zone Z1 is the sub-zone belong to zone Z2 and zone Z2 is the sub-zone within the whole area. Let us assume \( \eta_{Z1} \) is the Lagrangian variable corresponding to zone Z1 FRU requirement, \( \eta_{Z2} \) is the Lagrangian variable corresponding to zone Z2 FRU requirement, \( \eta \) is the Lagrangian variable corresponding to system wise FRU requirement. The same definition of \( \mu_{Z1}, \mu_{Z2} \) and \( \mu \) is applied for FRD requirement. The MCP of FRU for zone Z1 is \( \eta_{Z1} + \eta_{Z2} + \eta \), for zone Z2 is \( \eta_{Z2} + \eta \) and for rest of control area is \( \eta \). Similarly, the MCP of FRD for zone Z1 is \( \mu_{Z1} + \mu_{Z2} + \mu \), for zone Z2 is \( \mu_{Z2} + \mu \) and for rest of control area is \( \mu \).
\[ \sum_{i \in Z} FRU(i,t) \geq FRU_{req}(Z,t) \quad \forall Z,t \quad (\mu_Z) \] (5.10)

\[ \sum_{i \in Z} FRD(i,t) \geq FRD_{req}(Z,t) \quad \forall Z,t \quad (\eta_Z) \] (5.11)

### 5.2.3 Stochastic Economic Dispatch with nodal flexible ramping requirement

The objective of the Stochastic Economic Dispatch with nodal flexible ramping requirement is to minimize the binding interval energy cost and FRP procurement cost plus the stochastic look-ahead interval energy dispatch cost. The formulation for the objective function is shown as (5.12).

\[
\text{Minimize} \quad \sum_i C(g(i,t)) + C(FRU(i,t)) + C(FRD(i,t)) + \sum_s \sum_i C(g(i,t+1,s))
\] (5.12)

The Stochastic Economic Dispatch with nodal flexible ramping requirement includes the constraints (5.2)-(5.7) from the section 5.3.1. But the FRP requirement constraints (5.8)-(5.9) are replaced by the scenario based formulation (5.13)-(5.16).

1) Power balance equation with net load uncertainty:

\[
\sum_i g(i,t+1,s) = \sum_i d(i,t+1,s)
\] (5.13)

2) Power flow constraint with net load uncertainty:

\[
\sum_j SF_j (g(i,t+1,s) - d(i,t+1,s)) \leq f_{\text{max}} (l)
\] (5.14)

3) Maximum inter-temporal ramping limit:

\[
g(i,t+1,s) - g(i,t) \leq FRU(i,t)
\] (5.15)
\[ g(i,t) - g(i,t + 1, s) \leq FRD(i,t) \] (5.16)

In this model, only two intervals are considered as a two stage problem where the first interval is the binding interval and second interval is the look-ahead interval. The flexible ramping product is utilized to provide the ramping capability between the first interval and the look-ahead interval. The different combinations of uncertainties at each bus are considered as different scenarios and the transmission line flow limit at each scenario is considered as (5.14) so that the ramping capability is not only sufficient in capacity but deliverable for each scenario.

### 5.2.4 Net Load Uncertainty Set

Assuming the net load uncertainty is a symmetrical polyhedral set. Then the net load deviation from the forecast value can be expressed as (5.17) where the \( \Delta d_{\text{max}}(i) \) is the maximum net load deviation at each location \( i \) which is based on the historical statistical analysis.

\[
|\Delta d(i,t)| \leq \Delta d_{\text{max}}(i) \] (5.17)
In [62], a budget of uncertainty is introduced to limit the total deviation of the net load as (5.18). This constraint limits the combined deviation of net load with a parameter \( \gamma \in [0, N_i] \) where \( N_i \) is the total number of buses with uncertainty, in other words, the net load realization cannot be at the upper or lower bound of the uncertainty set simultaneously. This reflects the correlation between the uncertainty sources. Fig 5.2 illustrates the polyhedral uncertainty set for two wind farms. In [62], the proof is given that the worst case solution must be located on the vertices of the uncertainty set. So we can narrow the worst case scenario down to a limited number of vertices. In the robust optimization, the objective function minimizes the cost for the worst case scenario, but in the proposed model, the worst case scenario is replaced by the limited number of scenarios on the vertices of the uncertainty set.

\[
\sum_{i} \frac{\Delta d(i,t)}{\Delta d_{\text{max}}(i)} \leq \gamma
\]  
(5.18)
5.3 Solution Methodology

The stochastic problem is computationally expensive due to its significant size with a large number of scenarios. And it has some complicating variables which do not allow us to solve the problem by block separation. The L-shape method [40] provides us an algorithm to solve the problem with complicating variables by iterative fashions. The problem is decomposed into a first stage master problem and several second stage sub-problems where each sub-problem represents a single scenario problem.

The two stage stochastic optimization can be formulated as follows:

\[
\begin{align*}
\text{minimize} \quad & z = C^T x + \sum_s p_s D^T y_s \\
\text{s.t.} \quad & Ax \leq b \\
& Tx + Wy_s \leq h_s \quad \forall s \in S \\
& x \geq 0, \quad y_s \geq 0
\end{align*}
\] (5.19)

where \( C \in R^{n_1} \), \( b \in R^{m_1} \) and \( D \in R^{n_2} \) are the known vectors, \( A \in R^{m_1 \times n_1} \), \( T \in R^{m_2 \times n_1} \) and \( W \in R^{m_2 \times n_2} \) are the known matrices. \( h_s \in R^{m_2} \) is the uncertainty vector, \( x \in R^{n_1} \) is the first stage decision variable, \( y_s \in R^{n_2} \) is the second stage decision variable, \( p_s \in R \) is the probability of each scenario \( s \), \( S \) is the uncertainty set. The L-shape algorithm is illustrated as follows:

Algorithm: L -Shaped Method

Step1: Solve the master problem (5.20) and obtain the lower bound solution \( z_{\text{lower}} \) at \( \hat{x} \) and \( \hat{Q} \). Since in the first iteration, \( Q_s \) is unconstrained, so simply let \( \hat{Q} \) be \(-\infty\), only minimize over the constrained variable \( x \).
\[
\begin{align*}
\text{minimize} & \quad z = C^T x + \sum_s Q_s \\
\text{s.t.} & \quad Ax \leq b \\
& \quad x \geq 0 \\
\end{align*}
\] (5.20)

**Step2:**

For \( \forall s \in S \), Do:

If the sub-problem (5.21) is infeasible, then let \( \hat{u}_s \) be the extreme ray of the dual of (5.21), and generate the feasibility cut (5.22).

\[
\begin{align*}
\text{minimize} & \quad D^T y_s \\
\text{s.t.} & \quad W y_s \leq h_s - T \hat{x} \\
& \quad y_s \geq 0
\end{align*}
\] (5.21)

\[
\hat{u}_s^T T x \leq h_s^T \hat{u}_s \\
\] (5.22)

Else If \( p_s D^T \hat{y}_s > \hat{Q}_s \), then \( \hat{Q}_s \) is the unrealistic estimation of \( p_s D^T y_s \), then a optimality cut (5.23) is generated where \( \hat{u}_p \) is the optimal solution of the dual of (5.21).

\[
p_s (h_s - T \hat{x})^T \hat{u}_p \leq Q_s \\
\] (5.23)

**Step3:** Solve the updated master problem (5.24) and get the new lower bound solution \( z_{\text{lower}} \) at \( \hat{x} \) and \( \hat{Q}_s \). Go to step 2 again, if there is no feasibility cut and optimality cut generated, \( x^* \) and \( Q_s^* \) are the optimal solution.
\[
\text{minimize} \quad z = C^T x + \sum_j Q_j \\
\text{s.t.} \quad h_i^T x \leq \bar{h}_i \quad \hat{\alpha} \\
\quad p_s (h_s - T x)^T \hat{\alpha} \leq Q_s \\
\quad A x \leq b \\
\quad x \geq 0
\] (5.24)

5.4 Case Study

A PJM 5 bus system is tested to compare the performance of three afore-mentioned models: the economic dispatch with system-wise FRP requirement, the economic dispatch with zonal FRP requirement and the stochastic economic dispatch with nodal FRP requirement. The one line diagram is illustrated in Fig 5.3. There are 5 thermal generators, 3 loads, 2 wind farms and 6 transmission lines in the system. All the lines are assumed to be lossless and the transmission limit is 240MW. The generator characteristic is summarized at Table 5.1. Assuming no load uncertainty is considered, all the uncertainty comes from the wind forecast inaccuracy. The load forecast for the binding interval is 900 MW which is distributed to bus B, C and D at the ratio of 2:4:4. The load forecast in look-ahead interval is 930 MW with the same distribution factor. In the binding interval, both of the wind farms are forecasted to produce 150 MW and are assumed to be accurate. In the look-ahead interval, one wind farm at bus D is forecasted to generate 150 MW with 10 MW maximum forecast uncertainty, another wind farm at bus E is forecasted to generate 150 MW with 20 MW maximum forecast uncertainty. The budget of uncertainty parameter is assumed to be \( \gamma = 1.4 \). The uncertainty set has already been illustrated in Fig 5.2. There are eight worst case scenarios corresponding to eight vertices of the uncertainty set.
5.4.1 The economic dispatch with system-wise FRP requirement

In this model, a system-wise FRP will be procured to cover the possible future net load uncertainty. Assume the load forecast is certain and the load will ramp up from 900 MW in the binding interval to 930 MW in the look-ahead interval. It is assumed both wind farms cannot reach the maximum uncertainty simultaneously. So the worst scenario will be a total 24 MW upward or downward uncertainty. So the system-wise upward FRP requirement will be 60 MW which is the sum of 30 MW load ramp and 24 MW wind uncertainty and downward FRP requirement is 0 MW since net load in look-ahead interval is always greater than the binding interval. With the system-wise FRP requirement in place, the market solution is illustrated in Table 5.2. Since the G5 is the most expensive unit, so it dispatches at its minimum capacity and provide most of FRU capacity. G1 and G3 are the most expensive units so they are dispatching close to their maximum capacity and G2 and G4 are relatively expensive so they are dispatching near the minimum capacity. The energy bid price and FRP bid price are listed in Table 5.3. Since we only have one system-wise requirement, so the FRP price at each node is equal. At interval t+1, we assume wind farm 1 drops from
150 MW to 146 MW, wind farm 2 drops from 150 MW to 130 MW and load rises from 900 MW to 930 MW. So the units G1, G2, G3 and G5 will release their FRU capacity to make up the net load ramping uncertainty. After the deployment of all the FRU capacity, the network power flow is illustrated in Fig 5.4. It can be observed that the power flow on Line A-B is now at 246.8 MW which is higher than its maximum flow limit. In this case, the system operator has to either overload the transmission line, or trigger the constraint violation penalty price or even curtail the load. All the solutions will cause the economic loss and potential system unreliability. In other words, some portion of the FRU capacity is not deliverable under the extreme scenario. In next sub-section, the zonal FRP requirement is introduced to deal with the shortcoming of the system-wise FRP requirement and this method is currently adopted by the industry widely.

Table 5.1 Generator Characteristic

<table>
<thead>
<tr>
<th>Gen Name</th>
<th>Gen Bus</th>
<th>Pmin (MW)</th>
<th>Pmax (MW)</th>
<th>Energy Price ($/MW)</th>
<th>FRP Price ($/MW)</th>
<th>Ramp Rate (MW/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alta</td>
<td>A</td>
<td>40</td>
<td>110</td>
<td>14</td>
<td>2</td>
<td>2</td>
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<tr>
<td>Brighton</td>
<td>E</td>
<td>170</td>
<td>570</td>
<td>20</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Park City</td>
<td>A</td>
<td>40</td>
<td>100</td>
<td>15</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Solitude</td>
<td>C</td>
<td>100</td>
<td>520</td>
<td>30</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Sundance</td>
<td>D</td>
<td>50</td>
<td>200</td>
<td>40</td>
<td>5</td>
<td>10</td>
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</tbody>
</table>
Table 5.2 Dispatch Result with system-wise FRP requirement

<table>
<thead>
<tr>
<th>UNIT</th>
<th>G1 (MW)</th>
<th>G2 (MW)</th>
<th>G3 (MW)</th>
<th>G4 (MW)</th>
<th>G5 (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td>110</td>
<td>170</td>
<td>93.1</td>
<td>176.9</td>
<td>50</td>
</tr>
<tr>
<td>FRU</td>
<td>0</td>
<td>10</td>
<td>6.9</td>
<td>0</td>
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<tr>
<td>FRD</td>
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Table 5.3 LMP and FRP MCP

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</thead>
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<td>30</td>
<td>22.3</td>
<td>18.8</td>
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<tr>
<td>FRU</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>FRD</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Fig 5.4 Power flow after FRP deployment
5.4.2 the economic dispatch with zonal FRP requirement

From the last section, transmission limit on line A-B restricts the full deliverability of FRU. To solve this problem, the zone Z1 is circled to include bus B and C as shown in Fig 5.5.

![Diagram of a 5 bus system with one constrained zone.](image)

Fig 5.5 the 5 bus system with one constrained zone

A zonal FRP requirement is proposed in supplemental to the system-wise FRP requirement. Since the demand D1 and D2 compose 60% of the total demand, in order to cover the total expected load ramping in zone Z1, a 18 MW (60% of 30 MW total load ramping) zonal FRU requirement is incorporated into the formulation (5.1)-(5.9). The dispatch result with zonal FRP is illustrated in Table 5.4. The energy and FRP price is illustrated in Table 5.5. The FRP price for G4 is $10 which is higher than other generator since it is located in the reserve zone Z1. The power flow after the full deployment of FRP is illustrated in Fig 5.6. The power flow after FRP deployment is still within the transmission line limit and the FRU capacity is fully deliverable.
5.4.3 the stochastic economic dispatch with nodal FRP requirement
In this section, the stochastic economic dispatch with nodal FRP requirement is tested on the 5 bus system. Unlike the deterministic model, the stochastic model consider a combination of possible extreme scenarios and the nodal FRP requirement ensures the deliverability of FRP and allows the nodal pricing for FRP. In Table 5.6, the dispatch result of flexible ramping product with stochastic and deterministic wind forecast is compared. The total generation from G1-G5 is the same 600 MW for both deterministic case and stochastic case because the load and wind forecast are assumed to be accurate in binding interval. In deterministic case, the total FRU capacity is 54 MW and total FRD capacity is 0 MW. The cheapest unit G1 is dispatched to its maximum capacity, the second cheapest unit G3 is dispatched close to its maximum capacity but some headroom is reserved for providing FRU capacity. The most expensive unit G5 is dispatching at its minimum capacity. The second most expensive unit G4 is dispatch above its minimum capacity because the line flow is binding at line A-B at 240 MW and bus C has a large negative shift factor -0.54 which can offset the power flow in line A-B. The unit G2 is also dispatching at its minimum capacity. In stochastic case, the total FRU capacity is 54 MW which will cover the 30 MW load increase and 24 MW worst wind reduction scenario and it is distributed to each of the 5 generators. The cheapest unit G1 is dispatched below its maximum capacity in order to provide the ramp up capacity. The unit G2 is dispatched 6.6 MW higher than the deterministic case in order to provide 6.6 MW downward ramping capacity. The unit G3 is dispatched lower than the deterministic case for providing more ramp-up capacity.

Table 5.7 presents the stochastic economic dispatch result with and without transmission constraints. With transmission constraints consideration, the system requires a total 13.2 MW
flexible ramp-down capacity. In scenario 1, both of the wind plants W1 and W2 are producing more than forecasted, so the unit G2 has to be dispatched down to 170 MW and unit G3 has to be dispatched down to 83.4 MW to avoid the power flow violation on congested line A-B. So it is the reason why the unit G2 requires 6.6 MW downward ramping capacity and unit G3 requires 6.6 MW downward ramping capacity. If the transmission limit is not considered in the formulation of the flexible ramping product, the reserved ramping capacity may not be able to deliver due to the transmission congestion. For instance, in the scenario 7, when net load increases by 32 MW, if no transmission constraints are considered, the unit G1, G2 and G3 will ramp up 10 MW and unit G5 will ramp up 2 MW to make up the net load increase. However, the power flow in line A-B is increased to be 253.8 MW which is higher than the line flow limit 240 MW. So the flexible ramping product is not deliverable in some scenarios even if it is sufficient in capacity requirement.

Table 5.8 illustrates the expected locational marginal pricing (LMP) for look-ahead interval. The penalty cost for load shedding is set at $1000/MW and the line flow limit violation cost is set at $50/MW. With the stochastic economic dispatch and nodal FRP modelling, the expected LMP is lower than the deterministic model because the deterministic model does not consider the deliverability of FRP explicitly and it can trigger the transmission constrain violation penalty and cause the LMP to be higher than what it is in the nodal FRP model. When the total demand at time interval T+1 is increased from 930 MW to 970 MW, the deterministic model will trigger the power balance violation cost in scenario 5 and cause the price spike at more than $1000/MWh. The comparison of the expected LMP in
this case is illustrated in Table 5.9 and it shows that as net load ramp increase, the price difference between stochastic nodal model and deterministic model gets larger.

Table 5.6 Stochastic vs Deterministic Economic Dispatch with Flexible Ramping Product

<table>
<thead>
<tr>
<th>Unit</th>
<th>G1   (MW)</th>
<th>G2   (MW)</th>
<th>G3   (MW)</th>
<th>G4   (MW)</th>
<th>G5   (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stochastic</td>
<td>104.7</td>
<td>176.6</td>
<td>90</td>
<td>178.6</td>
<td>50</td>
</tr>
<tr>
<td>Deterministic</td>
<td>110</td>
<td>170</td>
<td>93.1</td>
<td>176.9</td>
<td>50</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unit</th>
<th>FRU1 (MW)</th>
<th>FRU2 (MW)</th>
<th>FRU3 (MW)</th>
<th>FRU4 (MW)</th>
<th>FRU5 (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stochastic</td>
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<td>10</td>
<td>10</td>
<td>25</td>
<td>3.7</td>
</tr>
<tr>
<td>Deterministic</td>
<td>0</td>
<td>10</td>
<td>6.9</td>
<td>0</td>
<td>37.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unit</th>
<th>FRD1 (MW)</th>
<th>FRD2 (MW)</th>
<th>FRD3 (MW)</th>
<th>FRD4 (MW)</th>
<th>FRD5 (MW)</th>
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<tr>
<td>Stochastic</td>
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<td>6.6</td>
<td>6.6</td>
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<tr>
<td>Deterministic</td>
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</table>
Table 5.7 Stochastic Economic Dispatch with and without network constraints

<table>
<thead>
<tr>
<th>Unit</th>
<th>G1 (MW)</th>
<th>G2 (MW)</th>
<th>G3 (MW)</th>
<th>G4 (MW)</th>
<th>G5 (MW)</th>
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</thead>
<tbody>
<tr>
<td>With network</td>
<td>104.7</td>
<td>176.6</td>
<td>90</td>
<td>178.6</td>
<td>50</td>
</tr>
<tr>
<td>W/O network</td>
<td>100</td>
<td>184</td>
<td>90</td>
<td>176</td>
<td>50</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unit</th>
<th>FRU1 (MW)</th>
<th>FRU2 (MW)</th>
<th>FRU3 (MW)</th>
<th>FRU4 (MW)</th>
<th>FRU5 (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With network</td>
<td>5.3</td>
<td>10</td>
<td>10</td>
<td>25</td>
<td>3.7</td>
</tr>
<tr>
<td>W/O network</td>
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<td>10</td>
<td>10</td>
<td>0</td>
<td>24</td>
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</tbody>
</table>

<table>
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<tr>
<th>Unit</th>
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<th>FRD3 (MW)</th>
<th>FRD4 (MW)</th>
<th>FRD5 (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With network</td>
<td>0</td>
<td>6.6</td>
<td>6.6</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>W/O network</td>
<td>0</td>
<td>0</td>
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</table>

Table 5.8 Comparison of expected LMP of look-ahead interval with 930 MW load in T+1

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</thead>
<tbody>
<tr>
<td>Stochastic nodal model</td>
<td>20.8</td>
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<td>34.7</td>
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<td>21.7</td>
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<tr>
<td>Deterministic model</td>
<td>25.2</td>
<td>38.1</td>
<td>35.7</td>
<td>28.9</td>
<td>25.9</td>
</tr>
</tbody>
</table>
Table 5.9 Comparison of expected LMP of look-ahead interval with 970 MW load in T+1

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</thead>
<tbody>
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<td>44.2</td>
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<td>31.5</td>
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<tr>
<td>Deterministic model</td>
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<td>185.0</td>
<td>178.7</td>
<td>161.2</td>
<td>153.2</td>
</tr>
</tbody>
</table>

In the stochastic programming, two important metrics are used to measure the cost and benefit of the stochastic programming: Expected Value of Perfect Information (EVPI) and Value of Stochastic Solution (VSS) [40]. EVPI is the difference between the expected cost of the stochastic solution with recourse and the expected cost of the deterministic problem with the perfect forecast. This value reflects the cost of reliability and security on one hand and the incentive for improving the forecast accuracy on the other hand. In the test case, assuming both of the wind farms have perfect forecast, the total expected cost for this deterministic problem with perfect forecast will be $28,502. While the total cost for the stochastic problem solution is $28,863. The difference between them, $361, is the Expected Value of Perfect Information (EVPI) and it reflects the cost for the reliability. When EVPI is too high, it means the wind forecast is not so accurate and the improvement should be more focused on the forecast technique. VSS is the difference between the expected cost of using the expected value solution and the expected cost of the stochastic problem solution. The expected value for both of the wind farms at look-ahead interval is 150 MW. The solution for the expected value problem has already been illustrated in Table II. But when the actual scenario is realized, the dispatch solution based on expected value may not have sufficient
ramping capability to balance the generation and net load. That will trigger constraint relaxations include the line flow relaxation or load shedding. Assuming the penalty cost for load shedding is $1000/MW and for line flow relaxation is $50/MW. Then the total cost of the expected value solution including the penalty cost will be as high as $35,846. The difference between the total cost of expected value solution and the total cost of the stochastic solution is the Value of Stochastic Solution (VSS). This value reflects the saving in cost under extreme scenario by using the stochastic programming.

5.4.4 IEEE 30 bus system

The data for an IEEE 30 bus system is taken from [63], and its single line diagram is shown in Fig 5.7. The system consists of 30 buses, 41 lines, 6 thermal units, 20 loads and 3 wind farms which are located at bus 8, 11 and 18. The operation cost of the 6 generators at buses 1, 2, 13, 22, 23, and 27 are set to be 10, 15, 30, 35, 40, and 45 in unit $/MWh. The ramp rates for 6 generators are 8, 8, 4, 3, 5 and 5.5 in unit MW/min.
Fig 5.7 One-line diagram for IEEE 30 bus system

We assume the load ramp up 40 MW from binding interval to next interval and there is no load forecast uncertainty since the short term load forecast is fairly accurate. The wind forecast uncertainty for three wind farms are 30 MW, 50 MW and 50 MW, the maximum uncertainty for three wind farms are 10 MW, 20 MW and 20 MW. The uncertainty budget parameter $\gamma$ is set as 2 which means at maximum 2 of 3 wind farms can reach their maximum uncertainty simultaneously. According to the budget uncertainty constraints (5.17) and (5.18), the uncertainty set can be expressed as (5.25):
\[
\begin{align*}
|\Delta w_1| & \leq 10 \\
|\Delta w_2| & \leq 20 \\
|\Delta w_3| & \leq 20 \\
\frac{|\Delta w_1|}{10} + \frac{|\Delta w_2|}{20} + \frac{|\Delta w_3|}{20} & \leq 2
\end{align*}
\] (5.25)

There are 12 vertices on the uncertainty set and each vertex represents one scenario in the stochastic economic dispatch model. The Table 5.10 lists all of 12 scenarios and the corresponding wind output.

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
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<td>40</td>
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<th>S11</th>
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<td>30</td>
<td>30</td>
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<td>30</td>
<td>70</td>
<td>30</td>
<td>70</td>
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</tbody>
</table>

The comparison of expected LMP and power flow in the look-ahead interval between proposed stochastic nodal FRP model and traditional deterministic model is illustrated in Fig 5.8. It can be observed that with the proposed stochastic nodal FRP model, the LMP in the look-ahead interval is generally lower than the deterministic model. The LMP at bus 8 and 11
In this chapter, a stochastic look ahead economic dispatch with flexible ramping product is proposed. The case study demonstrates its effectiveness in handling the possible future worst case scenario, also, the transmission constraint modelling guarantee the deliverability of the proposed flexible ramping product. The L-Shape method is applied to solve large scale two-stage problem with high computational efficiency. In this chapter, only two intervals, binding interval and look-ahead interval, are modelled as a two-stage problem and only two wind farms are modelled as the source of uncertainty, it may be extended to multi-interval look-ahead problem using multi-stage problem and multi-dimensional polyhedral uncertainty set considering more uncertain sources. In addition, the correlation between the different wind farms could also be considered in shaping the uncertainty set. Also it is observed that in
the stochastic economic dispatch model, there is no explicit constraint for modelling flexible ramping product requirement, so the pricing scheme of flexible ramping product is still need to be further studied in the future work.
CHAPTER 6 SUMMARY AND FUTURE WORK

6.1 Summary of the dissertation

In this dissertation, the frequency responsive reserve requirement under high renewable penetration is proposed to achieve the satisfactory MW-frequency control performance. In chapter 2, the ED model with primary and secondary frequency constraints is proposed in tackling the frequency deviation under contingency situation. The frequency control performance with frequency constrained ED is compared with the traditional ED. It was found that frequency constrained ED performs better in various control performance metrics, such as nadir frequency, nadir time, nadir based frequency response and settling time. In chapter 3, the inertial, primary and secondary frequency reserve requirement is determined by integrating the frequency dynamics into the UC formulation. The stochastic feature of generator outage and wind ramping are also modelled to provide the robust solution toward different unit outage and wind scenarios. The demand side frequency response is also modelled to improve the frequency performance when the reserve from thermal units is insufficient. It was found that with demand side frequency responsive reserve, the reserve requirement from conventional thermal units is largely reduced so that the total reserve procurement cost is reduced. In chapter 4, the regulation reserve requirement under normal operation condition is considered. The MLR model is used to determine the regulation reserve requirement with target CPS1 score and forecasted load and wind condition. The case study shows that, with the proposed regulation requirement method, a number of benefits can be achieved comparing with the other reserve requirement practices: 1), the CPS1 score is less volatile, 2), the NERC CPS1 requirement is satisfied, 3), the total procurement cost is
reduced. In chapter 5, the FRP requirement is proposed under three different system model:
1), the economic dispatch model with system-wise FRP requirement, 2), the economic
dispatch model with zonal FRP requirement, 3) a stochastic look ahead ED with nodal FRP
requirement. The case study demonstrates that the third model outperforms the other two
models in its effectiveness to handle the future worst case scenarios and the ability to
incorporate the transmission constraint to guarantee the deliverability of the FRP. The L-
Shape method is applied in the third model to solve large scale two-stage stochastic problem
in an efficient and effective way.
6.2 The integrated market structure model

The previous chapters cover a wide range of frequency responsive reserves which cross
the entire time spectrum from seconds to hours, including the regulation reserve and FRP
under the normal operation condition, and the IR, PFR and SFR under the N-1 contingency
condition. The proposed approached for determining the new reserve requirement can be
integrated into a single market structure where the stochastic unit commitment is modelled
by considering the combination of generation trip and net load ramping scenarios. The IR,
PFR and SFR are procured to recover the frequency deviation after the generation
contingency or severe net-load ramping event. The regulation reserve requirement and FRP
requirement is used to ensure the balance between generation and load from second-to-
second to sub-hourly time frame. The all-in-one market structure model can be formulated as
a single abstracted economic dispatch model while considering co-optimization between
energy and each type of ancillary service and the interdependency between them:

\[
\text{minimize } \sum_i C(g_i) + \sum_i C(PFR_i) + \sum_i C(SFR_i) + \sum_i C(REG) + \sum_i C(FRP_i) \quad (6.1)
\]
\[ g_i + PFR_i + SFR_i + REG_i + FRP_i \leq P_{i,\max} \quad \forall i \] 
\[ g_i - REG_i \geq P_{i,\min} \quad \forall i \] 

\[ \sum_i REG_i \geq REG_{req}(CF_{1,\text{net}}, \text{netload}, \text{Hour}) \] 

\[ \sum_i FRP_i \geq FRP_{req}(\Delta \text{netload}) \] 

\[ \begin{align*}
    f_{\text{min}}(\text{IR}, PFR) & \geq f_{UFLS} \\
    ACE_{10\text{min}}(SFR) & = 0 \\
    \text{other } \text{IR, PFR, SFR} \text{ related constraints}
\end{align*} \] 

Here the objective of the integrated market model (6.1) is to minimize the total operation cost for energy, PFR, SFR, regulation and FRP. In (6.2), each type of ancillary service is allocated to share the available capacity of resource between its Pmin and Pmax. Equation (6.3) represents the requirement for regulation reserve based on target CF1 score, forecasted net load condition and hour of the day and it is the main content covered in Chapter 4. Equation (6.4) is the requirement for FRP which is based on the forecasted inter-temporal net load ramp and it is the major content of Chapter 5. The formulations (6.5) represent the constraints related to IR, PFR and SFR which are mainly covered in Chapter 2 and 3. The integrated market model (6.1)-(6.5) co-optimize the energy, regulation, PFR, SFR and FRP and meet the frequency performance under normal and contingency condition.

6.3 Future work

With the benefits and advantages achieved from the aforementioned models, there are still some areas needs to be further explored in future research.
1) The chapter 2 and 3 introduce the ED and UC model to co-optimize the energy and inertial, primary and secondary frequency reserve. The model provides the possible market mechanism to procure the inertial and primary frequency reserve in the market environment which is not currently implemented in US electricity market. In this dissertation, the pricing scheme and settlement scheme for inertial and primary frequency response is not explored thoroughly. Particularly for inertial and primary frequency response, many recommendations and advices have been proposed for setting up the associated ancillary service market. So a market mechanism allowing the units to offer the inertial and primary reserve bid via market environment instead of only reliability need will be necessary for the future research. Also the operation cost and opportunity cost associated with those two reserves has not been clear and requires further research and study.

2) The regulation reserve requirement based on CPS1 score and MLR approach is proposed. In that model, because of the data limitation, weekday/weekend, month and seasonal information are not considered in MLR model. It will be more accurate to include as much related information as possible and then use the feature selection technique to reduce the predictor number. Also, the regulation units are assumed to follow the AGC signal perfectly, but in the real system, many AGC units cannot respond perfectly as the AGC signal instructs and some units even respond in the opposite direction. Those uninstructed deviation can cause the significant degradation of frequency performance. Accurate modelling of the uninstructed deviation will be necessary to determine the regulation reserve requirement. Also in chapter 4, we mainly focus on the CPS1 as the output signal to
determine the regulation reserve requirement, while in the future research, CPS2 and BAAL can also be considered in regulation reserve requirement determination.

3) The model complication of the FRP is highly dependent on the dimension of uncertainty set and number of look-ahead intervals. The higher dimension of the uncertainty set, the more extreme scenarios the problem needs to include and the larger the size of the model is. To overcome this barrier, the robust optimization model [64] can be applied for higher dimensional uncertainty set to defend against only the most extreme scenario instead of a set of possible extreme scenarios as the stochastic model does. Similarly, when more look-ahead intervals the model includes, the size of the problem will increase significantly. So some advanced computational techniques should be used to resolve this difficult. The multi-stage L-shape method [40] can be one of them to solve the multi-stage problem in an iterative way and the Progressive Hedging Algorithm (PHA) [40] is another solution to solve the multi-stage problem based on scenario decomposition instead of stage decomposition in L-shape method.
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