

Flexible Reserve Margin Optimization for Increased Wind Generation Penetration

by

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ABSTRACT

Large-scale integration of wind generation introduces planning and operational difficulties due to the intermittent and highly variable nature of wind. In particular, the generation from non-hydro renewable resources is inherently variable and often times difficult to predict. Integrating significant amounts of renewable generation, thus, presents a challenge to the power systems operators, requiring additional flexibility, which may incur a decrease of conventional generation capacity.

This research investigates the algorithms employing emerging computational advances in system operation policies that can improve the flexibility of the electricity industry. The focus of this study is on flexible operation policies for renewable generation, particularly wind generation. Specifically, distributional forecasts of windfarm generation are used to dispatch a “discounted” amount of the wind generation, leaving a reserve margin that can be used for reserve if needed. This study presents systematic mathematic formulations that allow the operator incorporate this flexibility into the operation optimization model to increase the benefits in the energy and reserve scheduling procedure. Incorporating this formulation into the dispatch optimization problem provides the operator with the ability of using forecasted probability distributions as well as the off-line generated policies to choose proper approaches for operating the system in real-time. Methods to generate such policies are discussed and a forecast-based approach for developing wind margin policies is presented. The impacts of incorporating such policies in the electricity market models are also investigated.

DEDICATION

To my family

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NOMENCLATURE

- Acronyms

AGC	Automatic generation control
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
AR	Autoregression
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
CDF	Cumulative density function
CAISO	California independent system operator
DCOPF	DC optimal power flow
EENS	Expected energy not served
ELCC	Effective load carrying capability
ERCOT	Electric reliability council of Texas
FERC	Federal energy regulatory commission
FOR	Forced outage rate
IPP	Independent power producer
LCR	Level crossing rate
LMP	Locational marginal price
LOLP	Loss of load probability
NWP	Numerical weather prediction
PDF	Probability distribution function
RMP	Reserve marginal price

RPS	Renewable portfolio standard
RTS	Reliability test system
SCED	Security constrained economic dispatch
SCUC	Security constrained unit commitment
SVM	Support vector machine
QOS	Quality of service

- Mathematical Nomenclature

- Indices and Sets

g	Index of generators, $g \in G$.
$g(n)$	Set of generators connected to node n .
k	Index of transmission lines, $k \in K$.
n	Index of buses $n \in N$.
s	Index of scenarios, $s \in S$.
t	Index for time periods, $t \in T$.
w	Index of wind generators, $w \in W$.
$\delta^+(n)$	Set of lines specified as to node n .
$\delta^-(n)$	Set of lines specified as from node n .
Ω_g	Set of generators.
Ω_n	Set of buses.

- Parameters

B_k	Electrical susceptance of branch k .
C_c^n	Load curtailment cost at bus n (\$/MWh).

- C_g^e Operational cost of conventional unit g .
- C_g^{rc} Capacity cost of conventional unit g for providing spinning reserve.
- C_g^{re} Energy cost of conventional unit g for providing spinning reserve.
- C_p Penalty cost for wind farm if not able to abide by its scheduled output.
- C_w^e Operational cost of wind unit w .
- C_w^{rc} Capacity cost of wind unit w for providing spinning reserve.
- C_w^{re} Energy cost of wind unit w for providing spinning reserve.
- $F_w(\cdot)$ Cumulative density function (CDF) of w
- $L_w(\cdot)$ Level crossing rate (LCR) function of w
- N_w Number of states in \bar{S} .
- P_g^{max}, P_g^{min} Maximum output and minimum output of unit g .
- P_w^{max} Maximum output of wind unit w .
- P_k^{max} Maximum active power capacity of transmission line k .
- P_{wt}^f Point forecast of the output of wind unit w for period t .
- Per_{wt}^f Distribution forecast 90th percentile of wind unit w for period t .
- R_g^{10} 10-minute ramp rate of unit g .
- \bar{S} State space of Markov chain.
- \bar{U}_{gt} Scheduled unit commitment status of unit g in period t .
- Γ_k Wind farm generation at level k .
- π_s Probability of scenario s .
- τ_k Average duration of state k .

- Variables

$c_{base\ case,D}$ Cost for the base case in a deterministic structure.

$c_{base\ case,LS}$ Cost for the base case when a reduced number of scenarios are modeled.

$c_{PB,RS}$ Cost for the prediction-based method when a reduced number of scenarios are modeled.

d_{nt} Demand at bus n in period t .

ls_{nst}^+, ls_{nst}^- Violations in node power balance equation (load shedding) at bus n in scenario s for period t .

p_{gt} Scheduled real power output of conventional unit g in period t .

p_{kt} Real power flow of line k in period t .

p_{kst} Real power flow of line k in scenario s in period t .

p_{wt} Scheduled real power output of wind unit w in period t .

$p_{wst}^{penalty}$ Violation from the scheduled wind generation in scenario s for period t .

LP Load payment.

RAP_{gt} Reserve activation payment of unit g in period t .

r_{gt} Scheduled spinning reserve from conventional unit g in period t .

r_{gst} Actual exercised reserve from conventional unit g in scenario s for period t .

r_{wt} Scheduled spinning reserve from wind unit w in period t .

r_{wst} Actual exercised reserve from wind unit w in scenario s for period t .

rr_{gst} Residual reserve from conventional unit g in scenario s for period t .

rr_{wst} Residual reserve from wind unit w in scenario s for period t .

- α Flexible wind reserve margin policy factor.
- β Reserve adjustment factor.
- Δ_{wst} Uncompensated potential reserve from wind unit w in scenario s for period t .
- δ_{nt}, γ_{gt} Dual variables of power balance constraint and reserve capacity constraint.
- θ_{nt} Voltage angle at bus n in period t .
- θ_{nst} Voltage angle at bus n in scenario s in period t .
- $\lambda_{n,t}^c$ Dual variable of power balance constraint of bus n in contingency c in period t .
- ξ_{wt} Additional reserve required for period t due to the integration of wind unit w .
- σ_{wt} Variance of the output of wind generator w for period t .

CHAPTER 1

INTRODUCTION

1.1. Motivation and Scope of the Dissertation

Due to the recent technology and efficiency improvements as well as government financial support, the proportion of intermittent renewable resources in the generation mix is increasing. By the end of 2015, the worldwide installed wind capacity has reached 432.8 GW [1] and the installed capacity for solar has reached 227 GW [2].

As the penetration level of renewable generation increases, the electric industry looks for efficient solutions to enable large-scale integration of renewable resources. To accommodate the increasing generation from such resources, important changes are needed in both the planning and the operation aspects of power systems. Emerging developments in computational capabilities within the realm of smart grid provide promising solutions for planning and operation of the system in the presence of intermittent resources such as wind and solar energy.

This dissertation discusses the approaches the operators of power systems can use to deal with the uncertainty of generation from non-hydro renewable resources. The focus of this dissertation is on system operations, namely energy and reserve scheduling, in presence of wind generation. With the significant penetration of wind generation, the variability and uncertainty of wind energy requires the system to have additional flexibility.

Flexibility requirements in a power system are a function of grid infrastructure, the existing generation mix, and operating procedures. Demand response and energy storage are considered to be two major sources for increasing system flexibility in both planning

and operation procedures in power systems [3]. Energy storage can also take part in ancillary services markets both for regulation and operating reserves [59][4]. When studying the operational aspects, flexibility is usually described within the context of operating reserves, entailing the system to be able to balance out the deviations of the realized renewable generator output from its forecasted production.

Due to the uncertainty and variability of renewable generation, additional operating reserves may be needed to maintain the reliability of the system. Wind fluctuations increase requirements for rapid reserve, which may result in the scarcity of balancing services. While existing practices rely predominantly on conventional generators to provide the flexibility to sustain reliable operations, with the push to integrate more renewables, there is a need for a paradigm shift. Such a paradigm shift will be based on having the renewable resources behave similarly to the conventional generators. With the increasing share of renewable generation, it is expected that, in the future, these renewable resources will take part in providing ancillary services, too. It is worth mentioning that there is also a regulatory push for such a paradigm shift based on having renewable generators function similarly to conventional generators. As an example, FERC (Federal Energy Regulatory Commission) has proposed an order to eliminate the exemption for wind generators from the requirement to provide reactive power [5].

It is envisaged that renewable resources may be required to contribute towards the system balancing tasks. One approach is to provide operational flexibility by allowing for a discounted energy scheduling from wind generation. This will allow wind generators to provide a flexible reserve margin by withholding their own potential production in forward markets to hold some expected output. Excess wind can then be used as spinning reserve

to mitigate forecast errors and other system uncertainties. Dispatching the wind generator below the forecasted level offers a higher degree of flexibility when operating the system.

This study focuses on the ability for wind generators to provide reserve (in the form of reserve margins) in order to address the challenge of integrating high levels of non-dispatchable resources into the grid.

One primary objective of this study is to determine the optimal amount of dispatch that such renewable resources can provide. The aim has been to use stochastic models of wind to develop an affine policy function for scheduling energy and reserve from wind generators that strikes a balance between the operating costs and the risk associated with the mismanagement of wind generation that leads to an imbalance between demand and supply.

Subsequently, the focus of the work has been on developing scheduling and reserve policies when multiple dimensions of uncertainty are involved in the operating conditions of the system. Uncertainty complicates the process of economic dispatch and reserve scheduling for the system and renders the deterministic optimization approach less effective. The existing optimization approaches for handling uncertainty, such as scenario-based stochastic programming and robust programming, are often computationally expensive and hence, are less practical for making real-time operation decisions. This study investigates the possibility of exploiting offline stochastic calculations for training deterministic operation policies. Such deterministic policies are then applied to real-time system models to find the optimum dispatch and reserve schedule. An offline policy generation technique is proposed based on stochastic reserve margin scheduling to hedge against the real-time uncertainty of wind farm generation. Such offline analysis allows for modeling a broader range of uncertainty, making it applicable when there are multiple sources of uncertainty.

1.2. Organization of the Dissertation

The rest of this dissertation is organized as follows:

Chapter 2 provides a background review on the topics included in this dissertation. First, a brief review of wind power forecasting approaches is presented. The existing short-term wind power forecasting techniques and their general methodologies are discussed. Subsequently, the detailed procedure of the Markov chain model-based wind generation forecast, which is the method used for generating wind scenarios in this thesis, is described.

In chapter 3, a combined dispatch and reserve scheduling policy is proposed by determining a flexible wind reserve margin. In order to provide a flexible reserve margin, wind generators under-schedule in the hour-ahead energy market to hold some expected output for reserves. Additional wind energy is then available for mitigating forecast errors and other system uncertainties. A framework is presented to find the optimal policy to incorporate the flexible wind reserve margin into the hour-ahead market. A finite-state Markov chain wind power forecast model, based on spatio-temporal analysis, is utilized to find the appropriate level of wind reserve margin.

In chapter 4, the possibility of exploiting offline stochastic calculations for training deterministic operation policies is investigated. An offline policy generation technique is proposed, based on stochastic reserve margin scheduling, to hedge against the real-time uncertainty of wind farm generation. The proposed policy generation structure is developed in a forecast-based framework by taking into account both the wind generation status and the loading conditions of the system. The proposed approach is tested and the costs are compared to those obtained by using ad-hoc rules to analyze the effectiveness of the presented model in handling uncertainty.

Chapter 5 investigates the market implications of deploying the deterministic reserve policy based on the offline stochastic analysis. The bids of the generators for energy and ancillary services are considered. In addition, a market settlement scheme is proposed that can be used for the proposed policy. In the proposed structure, the generators are compensated for the energy and reserve that they provide. The reserve providers are compensated for both the reserve capacity and the reserve activation. The reserve activation payments are dependent upon the performance of the reserve resource for various uncertainty realization scenarios. The proposed approach is compared with a typical deterministic approach that does not use a reserve margin policy.

In chapter 6, conclusions are presented and future research directions are discussed.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

This chapter provides a background review for the main topics that are the focus of this dissertation.

2.1. Windfarm Generation Forecasting

With an expected high penetration level, wind generation integration is expected to impact the existing power systems operating procedures including, unit commitment, economic dispatch and ancillary services procurement. Compared to conventional generation (e.g., thermal, hydro, nuclear), wind generation has two distinct characteristics: variability and uncertainty. This is because wind power is dependent on the volatility of the wind. As a result, wind generation is considered to be semi-dispatchable meaning that the power output of a wind farm cannot be simply dispatched at the request of power system operators. To be specific, semi-dispatchable resources refer to intermittent resources that have a limited degree of controllability, unlike conventional generators that have full controllability. Due to the aforementioned characteristics, wind generation forecasting is critical to ensure that adequate resources for dispatch, ancillary services and ramping requirements are available all the time.

It is worth mentioning that wind power forecasting methods can be classified according to forecast time-scale [7]. Seasonal or long-term forecast is used for resource planning and contingency analysis. Day-ahead forecast is used for market trading and day-ahead unit commitment and scheduling. Short-term forecast is used for hour-ahead unit commitment, real-time dispatch, regulation and load following [7].

Due to the semi-dispatchability and uncertainty of wind, accurate forecasting models are needed to enable efficient integration of wind energy. The existing forecasting techniques for wind power can be categorized into a few broad categories [8]; physical methods, statistical methods, spatial correlation methods and artificial intelligence methods. Physical methods are based on numerical weather prediction (NWP) and use comprehensive weather data and advanced meteorological techniques for wind speed forecasting [9]-[10]. Generally, the detailed description of the weather is transformed to conditions at the location of the wind farm [11]. Such physical models need comprehensive calculations and are appropriate for long-term forecasting [12]. Statistical methods try to find the inherent relationship within the interdependent measured power data. These models include time-series approaches such as autoregressive (AR) models [13], autoregressive moving average (ARMA) [14], and autoregressive integrated moving average (ARIMA) [15]. Statistical methods are appropriate for short-term forecasting and their error increases as the prediction horizon is increased [12].

The spatial correlation models consider the impact of spatial relationship between various wind sites. In spatial correlation models, the wind speed measurement data at the prediction location, as well as the data for its neighboring points, are used to predict the wind speed.

The artificial intelligence based approaches have also been applied in forecasting wind speed and power. These methods include artificial neural network (ANN) [16]-[17], adaptive neuro-fuzzy inference system (ANFIS) [18]-[19], support vector machine (SVM) [20]-

[21], and evolutionary optimization algorithms [22]. There are also other hybrid approaches that take advantage of multiple forecasting methods by combining various individual models and their information [23]-[24].

A vast amount of work in the existing literature focuses on wind speed forecast, assuming that wind generation from the farm can be directly calculated as a function of wind speed at one specific location in the farm. In reality, however, the power outputs of wind turbines within the same wind farm can be quite different, even if the wind turbines are of the same class as well as being physically located close to each other. Therefore, forecast errors for existing approaches can be significant [25].

In this study, a spatio-temporal approach for wind power generation forecast is used, which takes into account the diurnal non-stationarity and the seasonality of wind [26]. Due to the inherent variability and uncertainty of wind farm generation, distributional forecast methods can manage the uncertainty better than point forecast methods. In this dissertation, a Markov chain model-based wind generation forecast is used based on the analysis provided by authors of [26]. Their model is used in chapter 3 and chapter 4 of this dissertation to generate distributional forecasts for wind generation. The critical observations and the principles of their forecast model are described in the following sections.

2.2. Spatio-temporal Dynamics of Wind Farms

A critical reported observation from the measurement data is the spatial dynamics [27]. The power outputs of wind turbines within a wind farm can be quite different, even if the wind turbines are of the same class and physically located close to each other [28]. Although the variable power outputs of wind turbines are not identical, it is assumed that they follow the same probability distribution if the wind turbines are of the same class.

Another key observation is the temporal characteristic, i.e. the diurnal non-stationarity and the seasonality of wind farm generation. The diurnal non-stationarity can be tackled by identifying a time epoch such that the wind generation exhibits stationary behavior within each epoch. The forecast model can then be developed for each of these epochs separately. According to [26], a three-hour epoch seems to be reasonable, i.e. the probability distributions of wind farm generation over three consecutive 1-hour intervals are consistent.

2.3. Markov Chain-based Short-term Forecasting

The procedure for developing the Markov chain short-term forecast is described in this section based on [26]-[28]. The objective is to address the statistical distribution and temporal dynamics of aggregate wind farm generation using a Markov chain.

In this approach, in order to capture the spatial correlation between the power outputs from the wind turbines, a minimum spanning tree is constructed based on graph theory. The spatial correlation between the individual wind turbines is determined by using a linear regression model. The probability distribution of the aggregate wind generation can then be characterized using the wind speed measured at the reference meteorological tower in the farm. The temporal correlation is analyzed by using a finite-state Markov chain model. The seasonality is tackled by designing the forecast model for each month individually.

Assume the Markov chain is discrete time, of order 1, and has N_w states. Let \bar{S} denote the state space of the Markov chain. Each state $S_k = [\Gamma_k, \Gamma_{k+1})$, $k \in \{1, \dots, N_w\}$ is defined as an interval of generation level, with extreme values given by $\Gamma_k = 0$ and $\Gamma_{N_w+1} = P_w^{max}$,

where P_w^{max} is the maximum generation of wind farm w . The finite-state Markov chain model is developed as follows:

Define the quantity τ_k as the average duration that P_w , wind generation, stays in state S_k ,

$$\tau_k = \frac{F_w(\Gamma_{k+1}) - F_w(\Gamma_k)}{L_w(\Gamma_{k+1}) + L_w(\Gamma_k)} \quad (2.1)$$

where $F_w(\cdot)$ denotes the cumulative distribution function (CDF) of the farm aggregate wind generation and $L_w(\cdot)$ denotes the level crossing rate. Level crossing rate is defined as the number of times per unit time that the farm aggregate power P_w crosses Γ_k in positive/negative direction only. The cumulative probability distribution F_w of farm aggregate wind generation is characterized based on the historical data of wind farm generation.

The level crossing rate is given by

$$L_w(\gamma) = \int_{-\infty}^{\gamma} Pr(P_w(t) > \gamma | P_w(t-1) = p_w) dF_w(p_w). \quad (2.2)$$

It is worth noting that τ_k plays a critical role in the Markov chain model and determines how well the stochastic random process P_w is captured. A small value of τ_k suggests that P_w is more likely to switch out of the state S_k within a time slot, i.e., nonadjacent transitions are more likely to occur, and hence the transitional behaviors of P_w are not captured efficiently by the discrete-time Markov chain. Large values of τ_k indicate that the quantization by the Markov chain is not fine grained, and the corresponding forecast would be less accurate. One objective of state space design is, thus, to make each τ_k fall into a reasonable range [29]. In order to do that, one way is to introduce a constant τ and find the N_w variables $\{\Gamma_2, \dots, \Gamma_w\}$ by solving (2.1) numerically with $\tau_k = \tau, \forall k \in \{1, \dots, N_w - 1\}$.

Once the state space \bar{S} is designed, the transition probabilities can be estimated as proposed in [30]. The probability of a transition from S_i to S_j is given by

$$Q_{i,j} = \frac{n_{ij}}{\sum_{k=1}^{N_w} n_{ik}}, i, j \in \{1, \dots, N_w\} \quad (2.3)$$

where n_{ij} is the number of transitions from S_i to S_j occurred in historical data. The representative generation level for each state S_k can be determined using the minimum mean square error principle, given by

$$P_{w,k} = \arg \min E \left\{ (P_k - P_w(t))^2 \mid P_w(t) \in [\Gamma_k, \Gamma_{k+1}] \right\} = \frac{\int_{\Gamma_k}^{\Gamma_{k+1}} p_w d F_w(P_w)}{F_w(\Gamma_{k+1}) - F_w(\Gamma_k)}. \quad (2.4)$$

Therefore, given the present wind generation state of the wind farm output, the distributional forecast of the wind farm generation in next interval is given by

$$Pr(P_w^{t+1} = P_{w,j} \mid S_w^t) = Q_{S_w^t, j}, \forall j \in \{1, \dots, N_w\}. \quad (2.5)$$

Using this framework, the probability distribution of the immediate future state of the wind farm output can be predicted based on the most recent state of the system. This probability distribution expresses the transition probability from the present state to the future state.

The scheduling framework modeled in this study is short-term in nature, since it deals with hour-ahead decisions for acquiring energy and reserve. To determine the short-term schedule, the short-term wind power forecast model based on the finite-state Markov chain model is used. This model predicts the windfarm generation in the next time epoch (10-minute) to be among a few defined states with certain probabilities, thereby improving the

tractability for stochastic programming. The analysis performed in the following chapters is based on this Markov chain-based forecast model.

CHAPTER 3

ONLINE POLICY FOR WIND POWER RESERVE MARGIN FOR FLEXIBLE ENERGY AND RESERVE SCHEDULING

3.1. Introduction

The share of wind energy generation in electricity supply is increasing due to recent technology and efficiency improvements as well as government financial support. Many states in the U.S. have adopted a renewable portfolio standard (RPS) and have started integrating renewable resources, such as wind, solar, biomass and other alternatives to fossil electric generation [31].

Due to the uncertainty and variability of renewable generation, additional operating reserves may be needed to maintain the reliability of the system. In order to operate the system in a secure and stable manner, sufficient reserve capacity must be in place to overcome load and renewable forecast errors or unexpected failures of generators. When renewable resources drop below their anticipated production level, fast acting up reserves should be called upon. When the actual wind generation is above the forecasted value, however, a different complication arises in terms of ramping down conventional generators. In some power systems, the operators are required to incorporate all the available wind power. Even in deregulated systems, the actual dispatched wind exceeds the cleared amount due to the low real-time price of the wind and lack of over-provision penalty. A significant amount of down reserve is needed, as a result, to balance these intermittent resources.

These operational aspects give rise to an interest in developing better approaches to determine the right amount and the location of reserve for systems with wind resources

[32]-[36]. In [37], a review of the different assumptions and methods used to calculate the amount of different types of reserves with high penetrations of wind power was presented. The authors of [38] used a stochastic optimal power flow to supplement traditional energy scheduling and reserve procurement while considering the uncertainty of equipment outages, errors in demand forecasts, and intermittent generation. Another work, [39], balanced the costs and benefits of spinning reserve while solving unit commitment. In that study, wind power forecast errors were modeled by a Gaussian distribution. The benefit was expressed as a function of the reduction in the expected energy not served (EENS). Recent work [40] used probability functions for conventional generator outages as well as discretized probability functions for wind power and load to create a distribution function of the system generation margin. Negative values represented cases where the generation is short. Essentially, they used a loss of load expectation (LOLE) threshold to calculate the required reserve to shift the generation margin curve to the right (positive direction). An overview of the current practices of operating reserves and methodologies used to estimate the increase in reserve allocation due to wind power was presented in [41].

As the wind penetration level increases, wind power producers are expected to behave similarly to other market participants, e.g., renewable resources may be required to contribute towards the system balancing tasks. Recent research works have investigated the possibility of having ancillary services from renewable resources. For instance, reference [42] discussed the capability of wind and solar plants to provide voltage regulation. The authors of [43], proposed to allow wind producers to participate in the regulation reserve market. They presented a strategy for the wind generator to bid into both energy and reserve markets. The authors of [44] used a similar market structure to show that a more secure

system operation with lower dispatch cost can be achieved in this new market setting. A real test on a wind farm in West Denmark was performed in [45] to analyze the participation of wind generators in the balancing markets. They found that the wind farm is able to play a proactive role in providing downward regulation and increase its profits. Electric Reliability Council of Texas (ERCOT) has revised its rules to require the wind generators to offer a minimum down balancing requirement based on their low and high sustainable limits [46].

The above studies presented specific structures to determine the required reserve from conventional generators to cope with the uncertainty of wind generation. While this approach is feasible, it will impose a high cost on system operations since sufficient flexible capacity must be on-line to manage the uncertainty of the wind production. Alternatively, a promising method is to allow wind generators to provide a flexible reserve margin by under-scheduling in forward markets. The concept of flexible wind reserve margin is a way to hedge against the uncertainty at an earlier stage. In order to provide a flexible reserve margin as proposed by [47], wind generators under-schedule in the hour-ahead energy market so as to hold some expected output as reserves. Excess wind can then be used as spinning reserve to mitigate forecast errors and other system uncertainties.

Dispatching the wind generator below the forecasted level allows for a higher degree of flexibility when operating the system. In addition, some renewable resources are semi-dispatchable and generally have no limits for ramping. Therefore, the system can benefit from greater availability of such fast reserves [48]. Based on this feature, renewable generators can be utilized to produce reserve capacity. The concept of wind reserve margin enables the windfarm generators to behave similarly to other generators and partake in the

system balancing tasks. Fig. 3.1 illustrates the concept of wind reserve margin. By withholding the potential output in the hour-ahead, the wind farm can mitigate the uncertainty related to the various possible realizations.

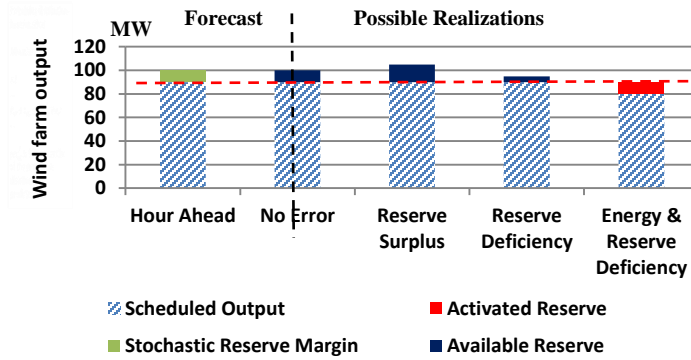


Fig. 3.1. Possible realizations with wind reserve margin.

The importance of operational flexibility is well recognized in the literature. Recent works have studied flexibility from both technical and economic perspectives [49]-[50] and proposed systematic definition for flexibility [51]-[52]. The dispatch framework introduced here is seeking to provide operational flexibility by allowing for a discounted energy scheduling from wind generation.

It is critical to analyze both the features of the wind power production and the reserve procurement approaches, as well as the associated tradeoffs, in order to ensure an efficient energy schedule and flexible wind reserve margin. As the operator relies on more wind energy production, the system faces more uncertainty, thereby requiring additional reserve. System reliability may be jeopardized if the wind energy production is less than what the operator anticipated. Thus, costly ancillary services and fast acting reserves have to be called upon to maintain the secure operation of the system. Dispatching a low level of wind, on the other hand, will result in inefficient utilization of wind power. The operational costs are, thus, expected to be higher since more energy will be scheduled from conventional

units. To address these tradeoffs, one must account for the scheduling costs and the risk imposed to the system due to the intermittency of renewable resources.

One primary objective of this study is to develop an affine policy for scheduling energy and reserve from wind generators that strikes a balance between the operating costs and the risk associated with the mismanagement of wind generation that leads to an imbalance between demand and supply. The main contributions of this study are summarized below:

- A risk-aware flexible joint dispatch and reserve scheduling model has been proposed, from the viewpoint of the system operator. The model minimizes the cost associated to providing adequate energy and reserves for the system, while satisfying the network constraints and abiding by the reliability and security criteria.

- A two-phase framework is developed to obtain appropriate policies for scheduling wind generation. In the first phase, a generation dispatch is performed to obtain the dispatch and reserve schedule for generation units. A scenario-based stochastic programming approach is leveraged to capture the effect of various possible wind scenarios. This initial phase minimizes the aggregate operating costs and risk costs relative to the modeled scenarios. In the second phase, the decision from the first phase is tested against a larger set of scenarios to ensure the adequacy of the scheduled energy and reserve.

- The performance of the risk-aware scheduling algorithm is compared with its counterpart without applying the flexible wind reserve margin policy. The results corroborate that the risk-aware scheduling can reduce the overall cost. Therefore, it is shown that the proposed structure effectively manages the forecast errors and achieves a more secure system dispatch.

The rest of this chapter is organized as follows. In section 3.2, the wind generation forecast model and scenario generation methodology are described. This section then explains the scenario reduction procedure used to come up with a set of representative wind scenarios. A joint energy and reserve scheduling model is proposed in section 3.3, where the two-phase policy determination procedure is described. Section 3.4 presents an illustrative case study, which quantifies the potential benefits of the proposed approach in both generation cost and spinning reserve cost based on a set of real generation data of a wind farm. The chapter is concluded in section 3.5.

3.2. Wind Generation Model

3.2.1. Short-term Wind Forecast Model

In this chapter, the Markov chain-based wind forecast model described in section 2.2.2 is used. This model takes into account the diurnal non-stationarity and the seasonality of wind [26]. Using this framework, the probability distribution of the immediate future state of the wind farm output can be predicted based on the most recent state of the system. This probability distribution expresses the transition probability from the current state to the future one.

The scheduling framework modeled in this study is for the short-term, since it deals with hour-ahead decisions for acquiring energy and reserve. To determine the short-term schedule, the finite-state Markov chain model is used. This model predicts the windfarm generation in the next time epoch (10 minutes) to be among a few defined states with certain probabilities, thereby improving the tractability for stochastic programming.

3.2.2. Wind Scenario Generation

In the current study, the short-term 10-minute wind generation forecast based on the finite-state Markov chain model is used to develop a scenario tree for the wind generation in the next hour, i.e., for the next six time intervals of 10 minutes. A scenario tree is generally represented by a finite set of nodes. It starts from a root node (state) at the first period and branches into nodes (states) at each next period. Every scenario represents a sequence of wind farm states, in the next six time intervals. The transition probabilities are derived using the finite-state Markov chain model developed based on the wind farm data. Fig. 3.2 shows the structure of the scenario tree for six time intervals. It is worth noting that the total number of scenarios remains in a reasonable range since the number of possible states in each 10-minute time interval is small.

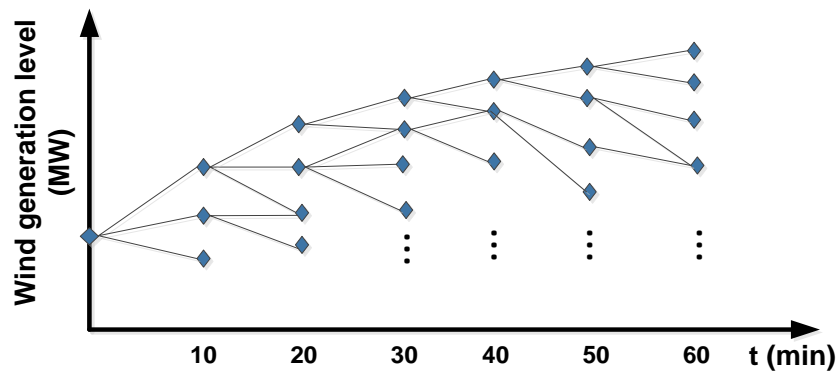


Fig. 3.2. Scenario tree generated for the next hour.

3.2.3. Scenario Selection

The computational effort for solving a scenario-based stochastic program depends on the number of modeled scenarios. In this study, in order to reduce the computational burden, a scenario reduction procedure is executed on the original set of scenarios. A clustering technique is used to come up with a few scenarios that properly represent the whole set

of scenarios. In this study, the technique introduced by [53] is used, which reduces the scenarios to their best approximation based on the Kantorovich distance of probability distributions.

For two discrete probability distributions P and Q , with scenarios $\xi^j, \tilde{\xi}^j$ and probabilities p_i, q_j respectively, the Kantorovich distance [53] is defined as,

$$D_k(P, Q) = \inf \left\{ \sum_{i=1}^S \sum_{j=1}^{\tilde{S}} \eta_{ij} C_T(\xi^j, \tilde{\xi}^j) : \eta_{ij} \geq 0, \right. \\ \left. \sum_{i=1}^S \eta_{ij} = q_j, \sum_{j=1}^{\tilde{S}} \eta_{ij} = p_i, \forall i, j \right\} \quad (3.1)$$

where $C_T(\xi^j, \tilde{\xi}^j) := \sum_{t=1}^T |\xi_T^j - \tilde{\xi}_T^j|, t = 1, \dots, T$ measures the distance between scenarios over the time horizon. If Q is the reduced probability distribution of ζ , the support of Q consists of scenarios ξ^j for $j \in \{1, \dots, s\} \setminus J$ where J represents the index set of deleted scenarios. For a fixed J , the scenario set Q that has minimal distance to P can be computed.

The minimal distance is

$$D_k(P, Q) = \sum_{i \in J} p_i \min_{j \notin J} C_T(\xi^j, \tilde{\xi}^j). \quad (3.2)$$

The new probability of a remained scenario equals the sum of its previous probability and the probabilities of deleted scenarios that were closest to it with respect to C_T . The optimal choice of an index set for scenario reduction with fixed cardinality is an optimal reduction problem that can be solved using the iterative algorithm in [53]. The algorithm omits one scenario at a time until the desired number of scenarios is achieved.

3.3. Joint Energy and Reserve Scheduling Based on Flexible Wind Reserve Margin

In this section, a scenario-based stochastic dispatch and reserve scheduling problem based on the short-term wind farm generation forecast is formulated. In the proposed struc-

ture, it is assumed that the market operator clears the energy and ancillary services simultaneously, rather than clearing them sequentially. This approach prevents the need for uneconomical out-of-merit operation, the start-up of extra generation units, and unnecessary load shedding [54]. The goal is to find the appropriate energy and reserve that can be scheduled from the wind farm to minimize the total cost. This total cost consists of the operational cost associated with procuring energy and reserve as well as the expected costs associated with inadequate appropriation of ancillary services. The focus is on the impact of wind generation uncertainty on system operation. The load uncertainty and forced outages of generators and transmission lines are not directly considered in this chapter.

The proposed procedure has a two-phase structure and aims to find the expected level of wind farm generation, relative to the predicted value, that the operator can utilize. It is assumed that the operator intends to perform the scheduling procedure for the next hour. This look-ahead dispatch allows for better planning of the resources, considering the 10-minute ramp up and ramp down capabilities of the conventional generators.

In this study, the expected amount of the wind generation that the operator can utilize is expressed as a fraction of the predicted wind generation for that hour. This fraction is referred to as the flexible wind reserve margin policy factor throughout this dissertation.

To find the best policy, the proposed two-phase procedure is performed for various factors. Initially, a certain fraction of the predicted wind generation is assumed to be utilizable. In the first phase, a stochastic program is solved. In the second phase, a risk analysis model is run to test the robustness of the first phase decisions. Section 3.3.1 and section 3.3.2 describe these two phases. The process is repeated for various policy factors in order

to find the optimal policy. The complete hour-ahead scheduling procedure can be viewed in Fig. 3.3.

As described above, the first phase uses a two-stage scenario-based stochastic program to deal with wind uncertainty where the scenario tree is generated by a Markov forecast model; note that other scenario tree generation techniques can be used instead. One primary tradeoff when choosing the right stochastic optimization approach is the model complexity (to ensure a high level of efficiency) versus the computational complexity. Interval-based stochastic programming could also be used within the first phase of the proposed policy function approximation approach; interval-based stochastic programming generates a scenario tree that is based on extreme events (in order to reduce the number of scenarios) whereas in this dissertation, a scenario reduction technique is used that takes into consideration the probabilities of scenarios. While both approaches can be used with the proposed technique, a scenario-based method, which accounts for the probabilities of the scenarios, has been employed. Since the Markov forecast model uses discrete states to describe the future, a scenario tree can be constructed based on the state transitions, encouraging the choice of scenario-based stochastic program for dealing with the uncertainty of wind during the first phase, which is solved offline.

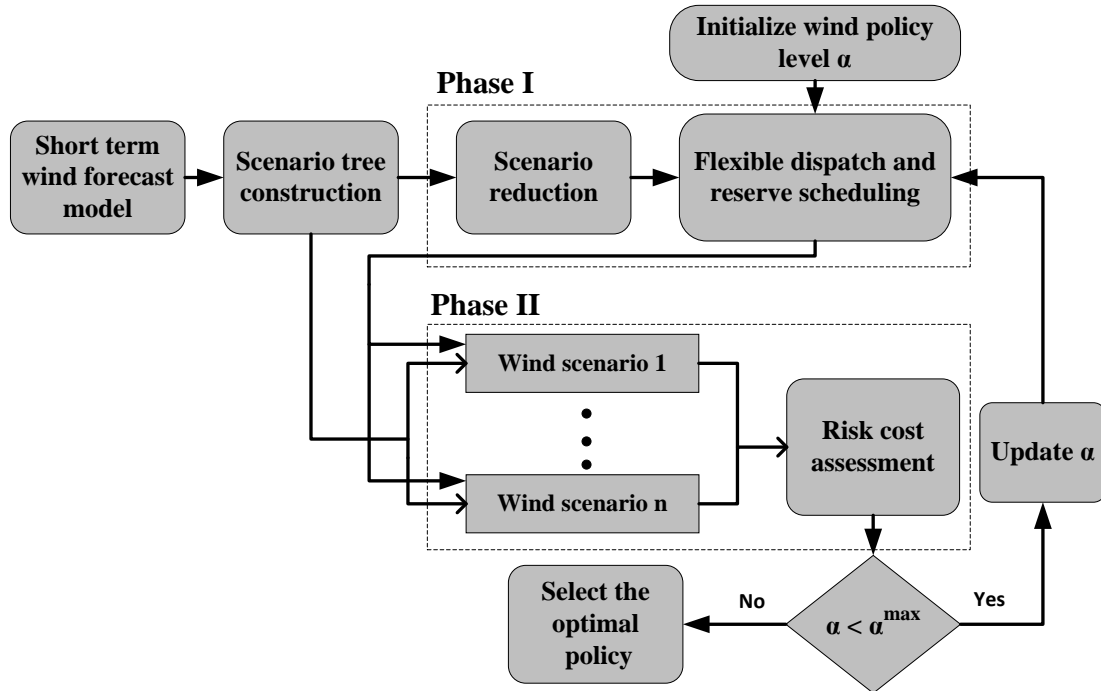


Fig. 3.3. Procedure to determine flexible wind reserve margin policy.

The scenario reduction technique introduced in section 3.2.3 minimizes the statistical distance between the original and the reduced probability distributions; hence, the scenario reduction technique finds the nearest reduced probability distribution in comparison to the original one. This reduction technique is, therefore, selected and employed in this dissertation to come up with an appropriate estimate of the cost that is expected on average for scheduling energy and reserve in the first phase. In order to handle the inaccuracy caused by the reduced representation of uncertainty, the effect of the full scenario set (including extreme scenarios) will be revealed in the second phase where the results are tested against all possible scenarios to ensure the robustness of the analysis that has been performed on the reduced set of scenarios.

3.3.1. Hour-ahead Risk-aware Energy and Reserve Scheduling

The proposed first phase model is a scenario-based stochastic program, which co-optimizes the energy and reserves for the base case. The second-stage ensures security based on the selected scenarios. The second-stage recourse function is, in fact, the cost of deploying available resources to maintain the system balance over various scenarios. The stochastic energy and reserve scheduling problem can be shown by (3.3)-(3.28),

$$\begin{aligned} \text{Min} \quad & \sum_{g,t}(C_g^e p_{gt} + C_g^{rc} r_{gt}) + \sum_{w,t}(C_w^e p_{wt} + C_w^{rc} r_{wt}) + \sum_{s,t} \pi_s \{ \sum_n C_c^n (ls_{nst}^+ + \\ & ls_{nst}^-) + \sum_w (C_p + C_w^{re}) p_{wst}^{penalty} + \sum_g (C_g^{re} r_{gst}) + \sum_w (C_w^{re} r_{wst}) + \sum_w (C_w^{rc} \Delta_{wst}) \} \end{aligned} \quad (3.3)$$

Subject to:

Base case constraints:

$$P_g^{min} \bar{U}_{gt} \leq p_{gt}, \forall g, t \quad (3.4)$$

$$p_{gt} + r_{gt} \leq P_g^{max} \bar{U}_{gt}, \forall g, t \quad (3.5)$$

$$0 \leq r_{gt} \leq R_g^{10} \bar{U}_{gt}, \forall g, t \quad (3.6)$$

$$\sum_{g \in G} r_{gt} \geq p_{gt} + r_{gt} + \sum_w \xi_{wt}, \forall g, t \quad (3.7)$$

$$\xi_{wt} \geq p_{wt} - (P_{wt}^f - \beta \sigma_{wt}), \forall w, t \quad (3.8)$$

$$p_{gt} - p_{g,t-1} \leq R_g^{10}, \forall g, t, \bar{U}_{gt} = 1, \bar{U}_{g,t-1} = 1 \quad (3.9)$$

$$p_{g,t-1} - p_{gt} \leq R_g^{10}, \forall g, t, \bar{U}_{g,t-1} = 1, \bar{U}_{gt} = 1 \quad (3.10)$$

$$p_{wt} + r_{wt} \leq \alpha P_{wt}^f, \forall w, t \quad (3.11)$$

$$p_{kt} - B_k(\theta_{nt} - \theta_{mt}) = 0, \forall k, t \quad (3.12)$$

$$-P_k^{max} \leq p_{kt} \leq P_k^{max}, \forall k, t \quad (3.13)$$

$$\sum_{g \in g(n)} p_{gt} + \sum_{k \in \delta^+(n)} p_{kt} - \sum_{k \in \delta^-(n)} p_{kt} + \sum_{w \in w(n)} p_{wt} = d_{nt}, \forall n, t \quad (3.14)$$

$$p_{wt}, r_{wt} \geq 0, \forall w, t \quad (3.15)$$

Second-stage constraints:

$$p_{kst} - B_k(\theta_{nst} - \theta_{mst}) = 0, \forall k, t \quad (3.16)$$

$$-P_k^{max} \leq p_{kst} \leq P_k^{max}, \forall k, t \quad (3.17)$$

$$\sum_{g \in g(n)} (p_{gt} + r_{gst}) + \sum_{k \in \delta^+(n)} p_{kst} - \sum_{k \in \delta^-(n)} p_{kst} + \sum_{w \in w(n)} (p_{wt} + r_{wst}) + ls_{nst}^+ - ls_{nst}^- = d_{nt}, \forall n, s, t \quad (3.18)$$

$$r_{gst} \leq r_{gt}, \forall g, s, t \quad (3.19)$$

$$-r_{gst} \leq r_{gt}, \forall g, s, t \quad (3.20)$$

$$P_g^{min} \leq p_{gt} + r_{gst} \leq P_g^{max}, \forall g, s, t \quad (3.21)$$

$$rr_{gst} = r_{gt} - r_{gst}, \forall g, s, t \quad (3.22)$$

$$-r_{wst} \leq r_{wt} + p_{wst}^{penalty}, \forall g, s, t \quad (3.23)$$

$$0 \leq p_{wt} + r_{wst}, \forall w, s, t \quad (3.24)$$

$$p_{wt} + r_{wst} + rr_{wst} \leq W_{wst}, \forall w, s, t \quad (3.25)$$

$$\Delta_{wst} \geq r_{wst} + rr_{wst} - r_{wt}, \forall w, s, t \quad (3.26)$$

$$\sum_{g \in g(n)} rr_{gst} + \sum_{w \in w(n)} rr_{wst} \geq p_{gt} + r_{gt}, \forall g, w, s, t \quad (3.27)$$

$$rr_{wst}, \Delta_{wst}, ls_{nst}^+, ls_{nst}^-, p_{wst}^{penalty} \geq 0, \forall w, n, s, t. \quad (3.28)$$

In the objective function (3.3), the first two summation terms represent the cost for scheduling energy and reserve capacity from generation units, including both conventional and wind generators. Note that in the proposed structure the generators would bid for both energy and reserve. The bid for reserve inherently reflects a lost opportunity cost estimated by the market participant. For a market environment, the generator will at least receive a

lost opportunity cost payment based on its reserve bid and if there are additional lost opportunity costs for a generator, they are handled by uplift payments.

For the case where there is an independent power producer (IPP) that holds a contract with a local utility (or some other entity), the bilateral contract dictates the terms of how lost opportunity costs are handled. Since lost opportunity costs are wealth transfers between two entities, the overall social welfare (market surplus) improvements that are presented in this dissertation will not change.

The remaining terms in the objective function express the expected cost incurred over the set of considered scenarios. This part includes the load shedding cost, the penalty cost associated with the wind farm not being able to abide by its scheduled output, the cost of exercised reserve in each scenario, and the cost of the residual reserve from the wind. This last term will be further explained in the description of the constraints. Please note that C_c^n would be set to a relatively high value to prevent load shedding/generation surplus as much as possible. For situations where additional wind production is not beneficial, it is assumed that there will be wind spillage, preventing the generation surplus to occur.

Equation (3.4) provides the lower bound on generation dispatch. Equation (3.5) provides the upper limit on the energy and reserve scheduled from a conventional unit. Equation (3.6) enforces the reserve scheduled from each unit for each time interval to be within the 10-minute ramping capability of the unit. Equation (3.7) presents the reserve requirement of the system; it indicates that the total reserve scheduled from conventional generation units should account for the outage of any single generator ($N-1$ reliability criterion) as well as a security margin added to account for the uncertainty of the scheduled wind energy.

Equation (3.8) presents the security margin considered for acquiring reserve in the presence of wind generation. Here, it is assumed that the operator should obtain additional reserve if the amount of scheduled wind is higher than a certain threshold. The threshold is set to be equal to the mean of the wind generation probability distribution function (predicted value) minus a factor β of the standard deviation. It is worth noting that this factor can also be used to set up a policy to determine reserve. A methodology similar to the one described for obtaining wind reserve margin can be applied for coming up with this reserve policy by addressing the trade-off between the scheduling and the risk costs. In the present study, however, this factor is assumed to be previously known and fixed, to avoid replicating the procedure.

Equations (3.9)-(3.10) show the ramp up and ramp down constraints for generators. Equation (3.11) sets the limit on the total energy and reserve that is scheduled from the wind generator. This limit is expressed as a factor α of the predicted value. This factor is referred to as the flexible wind reserve margin policy factor. Parameter P_{wt}^f is the point forecast of the output of wind unit w for period t and is determined by calculating the expected value of wind generation for each time period based on the scenarios generated.

Equation (3.12) describes the linearized line flow for each transmission asset. Equation (3.13) represents the transmission line operational limits. Equation (3.14) enforces the power balance at each node.

The second-stage constraints are intended to check the security of the first-stage decisions and must be satisfied for each of the modeled scenarios. Equation (3.18) enforces power balance in each node for each scenario. The second-stage generator outputs are based on the fixed first-stage generation dispatch plus the available reserve that is procured

from the first-stage. The load violation terms have been added to ensure the feasibility of the problem for all scenarios.

Equations (3.19)-(3.20) enforce the actual implemented reserve to be less than the amount scheduled in the first-stage. Note that r_{gt} is the amount of reserve procured for both the upward and downward directions and, hence, has a positive value. Variable r_{gst} is the actual exercised reserve and can be both positive and negative. Equation (3.22) shows the residual reserve from conventional units, which is the amount of acquired reserve in the first-stage that has not been exercised in the recourse stage. This residual reserve can count toward the $N-1$ reliability criterion.

Equation (3.23) states that if the implemented downward reserve happens to be greater than the amount scheduled in the first-stage (due to wind intermittency), it should be penalized (a penalty term is added to the objective). Note that it is also possible to have a violation of the upward reserve; for situations where additional wind production is not beneficial, it is assumed that there will be wind spillage. Equation (3.24) ensures that the implemented downward-reserve will not exceed the scheduled energy from wind. Equation (3.25) indicates that if the realization of wind is more than the amount used as energy and reserve in the second-stage, it can be considered as residual reserve and count towards the $N-1$ reserve criterion. Equation (3.26) shows the amount of potential reserve provided by wind unit in scenario s that has not been compensated for in the first-stage. Equation (3.27) conveys that the residual reserve after dealing with wind power uncertainty should suffice for satisfying the $N-1$ contingency reserve requirement.

The solution of this first phase determines the dispatch and reserve decisions, i.e., p_{gt} , r_{gt} , p_{wt} , r_{wt} . The optimal values of these variables are then fed as inputs to the risk analysis phase.

3.3.2. Risk Analysis Phase

The risk analysis phase is a verification of the first-stage decisions. In this phase, a deterministic model is used to test the first phase decision against every possible scenario in the scenario tree. Given the first phase decisions for energy and reserve schedule, the second phase tries to minimize the realized costs associated with each possible scenario, including the cost of exercised reserve, the penalty cost associated with the wind farm not being able to abide by its scheduled output, the cost of the residual reserve from the wind, and the load shedding cost. The model is formulated as follows:

$$\begin{aligned} \text{Min} \quad & \sum_t (\sum_g (C_g^{re} r_{gst}) + \sum_w (C_w^{re} r_{wst}) + \sum_w (C_w^{rc} \Delta_{wst}) + \sum_w (C_p + C_w^{re}) p_{wst}^{penalty} + \\ & \sum_n C_c^n (ls_{nst}^+ + ls_{nst}^-)) \end{aligned} \quad (3.29)$$

Subject to: constraints (3.16)-(3.28).

In this phase, p_{gt} , r_{gt} , p_{wt} , r_{wt} are fixed parameters determined in the previous phase. The risk analysis model is run for a larger number of scenarios to test the performance of the model from the first phase. The cost in this second phase is a measure of the risk imposed to the system operation by the decisions made in the first phase. If the decisions of the first phase are robust against the deterministic runs in the second phase, less cost would be incurred in this second phase.

3.3.3. Wind Scheduling Policy Determination

As mentioned in the previous section, parameter α is introduced into the dispatch structure to allow for determining the appropriate policy for scheduling energy and reserve from wind. Beginning with a small value for α , the optimization problem described in section 3.3.1 is solved. The obtained solution gives the optimum schedule as well as the operational cost for that specific value of α . The resulting energy and reserve schedule is then used as the input for the risk analysis problem described in section 3.3.2 to come up with the risk cost associated with that scheduling policy.

This procedure is repeated for various α values and the optimum operational and risk cost associated to each policy is recorded. The policy that has the minimum sum of the scheduling cost and the risk cost is expected to be the least-cost policy for scheduling energy and reserve from wind.

Note that the procedure to determine the flexible wind reserve margin policy factor involves running stochastic optimal power flows, which is computationally intensive. In this study, it is assumed that the policy determination procedure is performed offline and the resulting policy factors for various wind patterns are stored. In the hour-ahead operation, the operator would observe the realized wind generation and would then look for similar patterns in the offline procedure data to pick a strategy for scheduling wind based on the results of the offline study.

In the following simulations, it is assumed that the offline procedure is performed using the Markov chain model derived for the wind power generation based on data from the previous year, assuming that the current year wind generation is going to follow the same pattern as that of the last year.

3.4. Numerical Results

3.4.1. Test System and Simulation Setup

The proposed structure has been applied to the IEEE Reliability Test System (RTS)-96 [55]. It is assumed that each generator reserve bid is 15% of its energy bid. The test system is modified by integrating a 500 MW wind farm, at bus 4. The wind generation data of a wind farm for the year 2010 [26] is used after proper scaling to suit the chosen wind farm capacity. The average wind penetration (energy produced by wind generation / load capacity) is 7%.

Before running the hour-ahead dispatch, a deterministic day-ahead unit commitment (UC) is performed using the day ahead persistent point forecast to determine the commitment schedule for the 24-hour horizon. The restrictions, such as the minimum up and down time limits, are enforced in this stage. While it is assumed that wind is not allowed to provide reserve within the day-ahead UC model, the proposed model is amenable to such a day-ahead UC solution. The resulting on/off status of the generators is fed into the modeled hour-ahead energy and reserve scheduling program.

The optimality gap for the unit commitment problem has been set to 0.01. The original problem has 7128 binary and 9360 continuous variables, with 42278 constraints. This is decreased to 7008 binary and 9184 continuous variables with 26086 constraints in the reduced MIP problem. The resulting on/off status of the generators is fed into the modeled hour-ahead energy and reserve scheduling program.

The hour-ahead model includes 10-minute intervals across a 1-hour horizon. For the present simulation, the finite-state Markov model of the spatio-temporal analysis for the 9 AM-12 AM epoch is used since the output of the wind farm exhibits a high variability in

this epoch [26]. In this section, the hour-ahead scheduling has been performed for four typical days in different seasons. The wind scenarios are generated in a scenario tree format for the next six time intervals, i.e., a 6-stage scenario tree is constructed. As explained in section 3.2.2, in each stage a set of branches are added to the tree to represent the possible transitions to the next interval based on the 1-step Markov chain transition matrix. Due to the strong time-correlation that the wind data exhibit, the number of probable paths of this tree stays within a reasonable range (about 3000 scenarios for a 100-state Markov model, instead of 100^6). For the first phase, i.e., the stochastic programming phase, the number of scenarios is further reduced using the clustering algorithm described in section 3.2.3 and a total of 50 scenarios are considered. The standard deviation factor for (3.8) is set to 1 ($\beta=1$). The problem is a linear program; existing commercial grade linear programming solvers can efficiently handle this security constrained economic dispatch (SCED) problem today for large-scale systems.

In the second phase, the risk analysis model is run for all the possible scenarios. The optimal policy is determined based on the results obtained from these two phases.

All simulations are performed using the Gurobi solver in AMPL environment on an Intel (R) Core (TM) i7-3770 CPU @3.4 GHz computer with 16 GB of memory. The solution time is of the order of a few seconds for each scheduling run in the first phase and less than 0.1 second for each risk analysis run in the second phase. Furthermore, the resulting real-time SCED model is still a deterministic program, which is the same as what is used today in actual real-time market structure.

3.4.2. Results and Discussion

Starting from an initial wind policy, the first and second phase optimizations are solved for various values of α as described in section 3.3. These simulations started from a no wind policy ($\alpha = 0$), but the initial policy can be set to a higher value, e.g., the minimum predicted level in the scenario tree to speed up the process. The simulation results for the 9 AM-10 AM epoch of August 1st are plotted in Fig. 3.4. As Fig. 3.4 shows, the scheduling cost decreases monotonically as the expected utilizable generation from wind is increased. The reason is that more energy is scheduled from the cheap wind generators. The risk cost, however, increases with α since, by scheduling more wind, there will be a higher probability of not being able to supply the load. In other words, there are more instances that the actual wind is less than what is counted on in the first-stage. The figure suggests that, for the simulated hour, the total cost of the two stages reaches its minimum around $\alpha=0.8$, i.e., when the total scheduled energy and reserve is 0.8 times the mean predicted value. Figures 3.5, 3.6 and 3.7 show the scheduling cost versus the risk cost for the same time interval on three other days in other seasons. The optimal policy factor α is different for different months, ranging from 0.7 to 1.1, but the trends are similar in all of the figures. Note that in this procedure, the simulations are performed for a discrete set of values for α and thus, the lowest total cost found in this way is not the exact minimum cost for the continuous range of α .

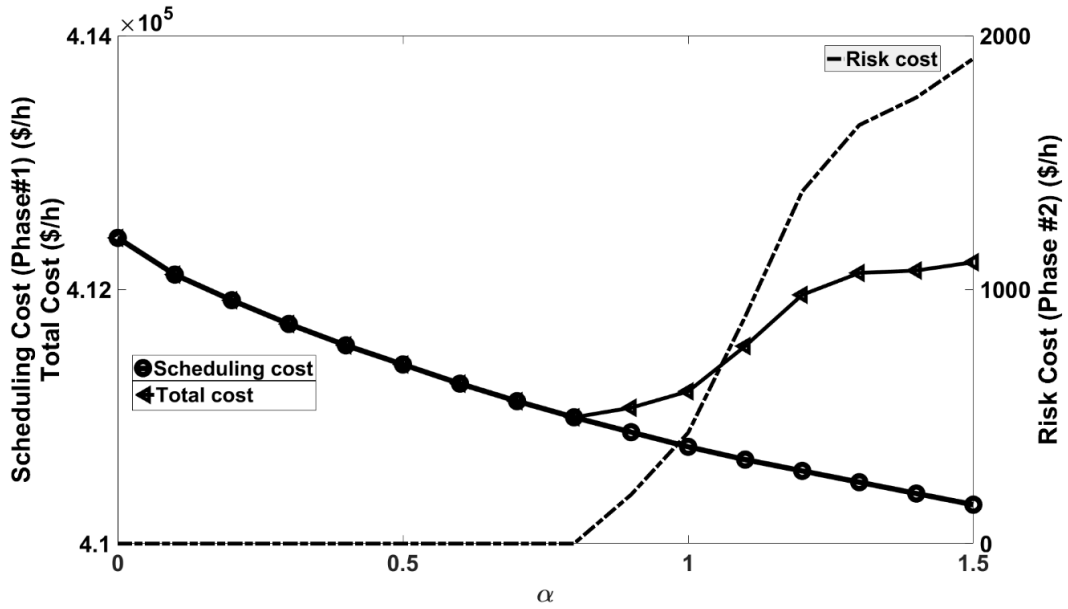


Fig. 3.4. Scheduling cost and risk cost as a function of the flexible wind reserve margin policy factor (August).

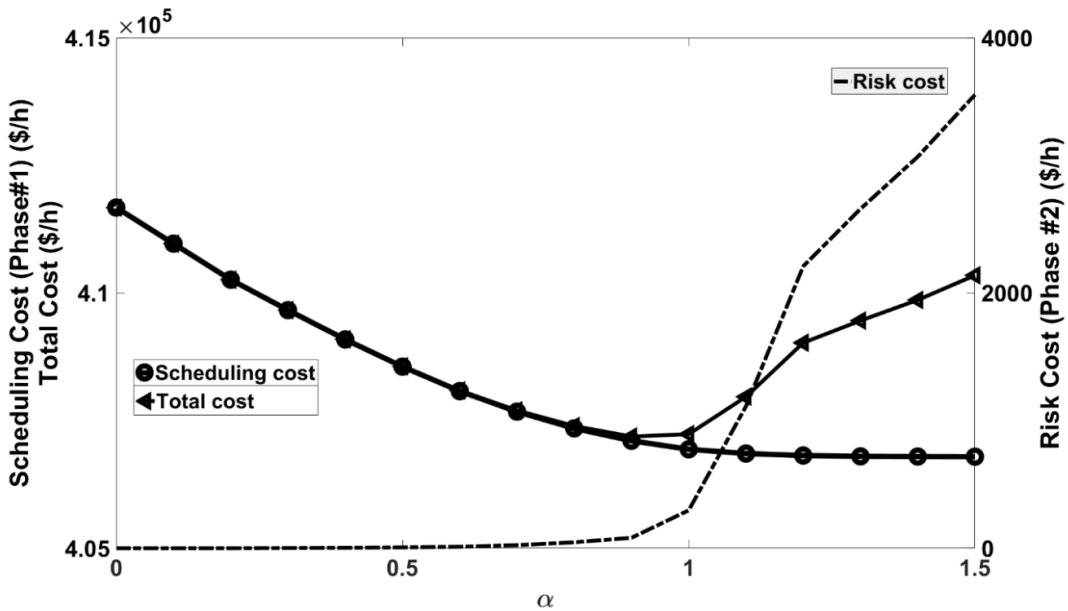


Fig. 3.5. Scheduling cost and risk cost as a function of the flexible wind reserve margin policy factor (October).

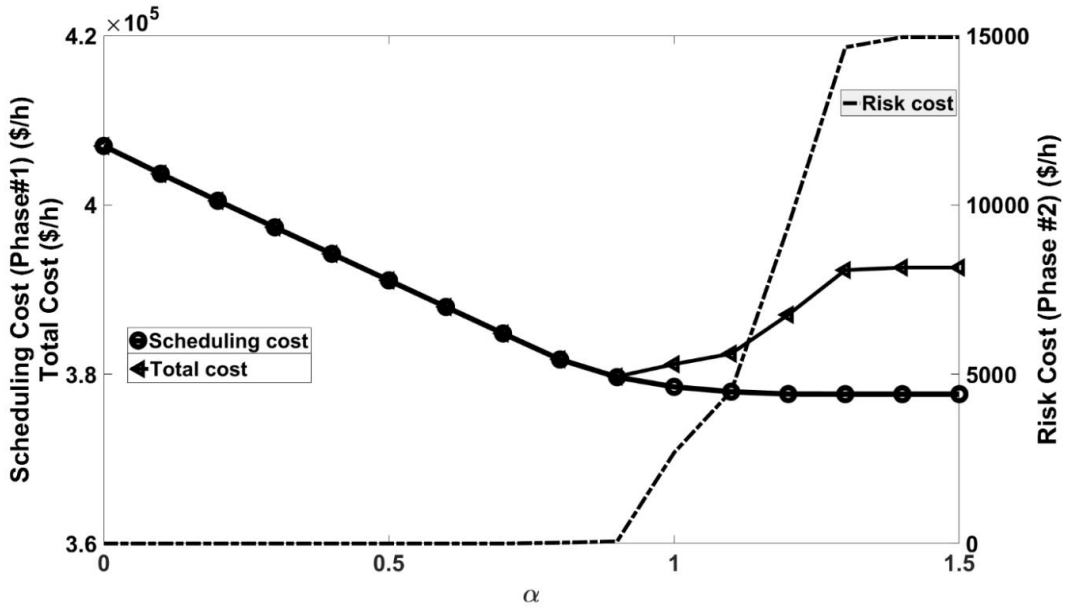


Fig. 3.6. Scheduling cost and risk cost as a function of the flexible wind reserve margin policy factor (February).

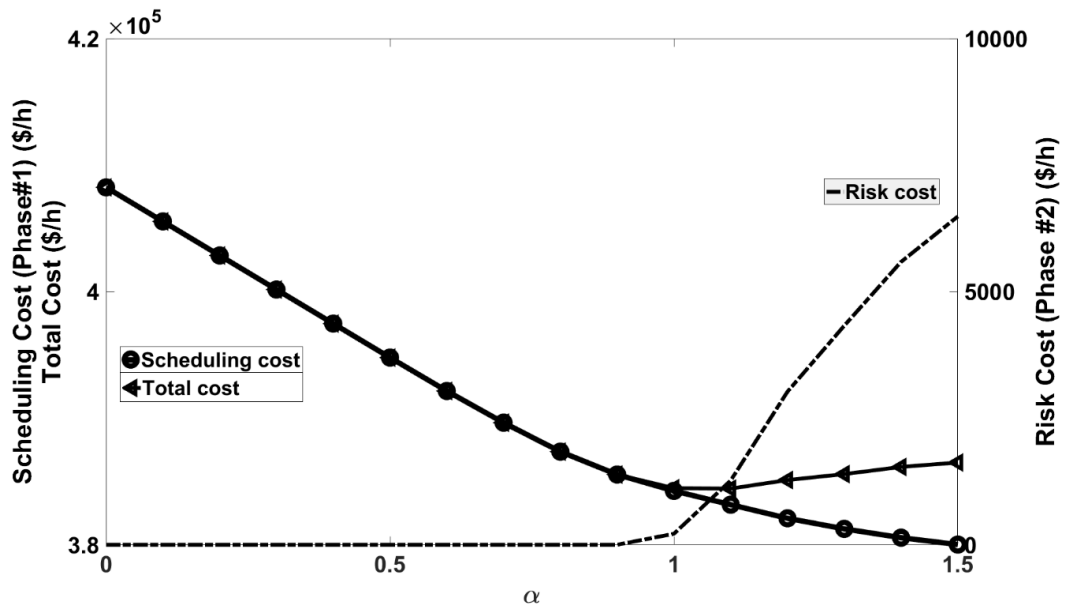


Fig. 3.7. Scheduling cost and risk cost as a function of the flexible wind reserve margin policy factor (April).

Fig. 3.8 presents the scheduled online generation and reserve from wind unit for the six future 10-minute intervals, with respect to the predicted value. Note that the energy

scheduled from the wind is below the forecasted mean but the total energy and reserve scheduled from the wind can go above the forecasted mean to provide an opportunity of using extra wind for balancing tasks. Also, note that as explained earlier, a scenario tree structure has been used for deriving the future possible scenarios. The number of possible outcomes increases as we move forward in the scenario tree. Hence, the standard deviation of the forecast error increases with the prediction horizon. As a result, the operator is less confident about the outcome of the wind farm and commits less energy and instead more reserve from wind generation in later time intervals as suggested by Fig. 3.8.

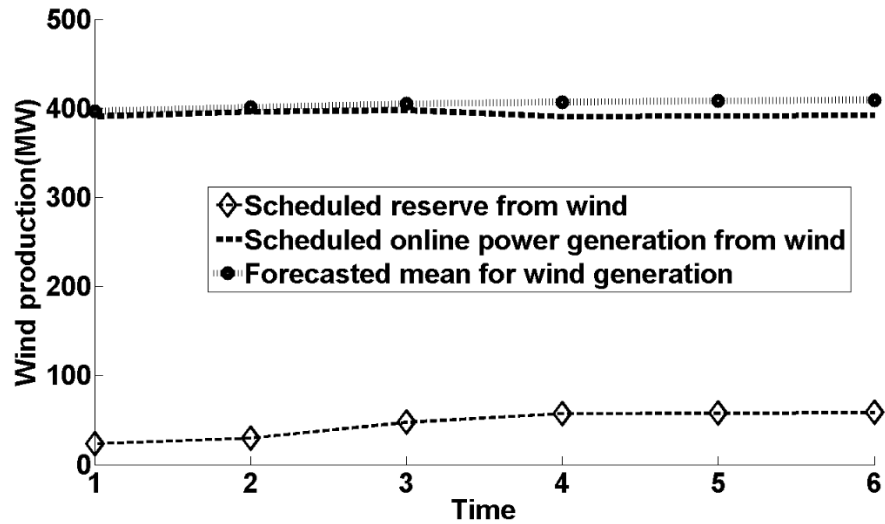


Fig. 3.8. Scheduled online power generation and reserve from wind vs. the forecasted level.

As described in section 3.3.3, the stochastic procedure to determine the wind policy is performed offline. To evaluate the actual performance of the selected policy, the obtained policy needs to be tested against real-time data. In this study, the data for a specific hour of one day have been used to come up with the optimum policy factor. For this particular example, it is assumed that the determined policy based on this offline analysis is then used

for the same hour in the following day. Fig. 3.9 shows the simulation results for the first week in October. The results are compared to a benchmark policy for the assumed set of scenarios; this benchmark policy would be obtained if the operator had the ability to run this offline approach in real-time. As Fig. 3.9 suggests, using the proposed forecast based policy can decrease the operational costs compared to the case where no flexible wind reserve margin policy factor is applied. The forecast based policy also performs well relative to the benchmark, without imposing the same real-time computational burden to the system.

Fig. 3.10 illustrates the amount of energy and reserve under different wind penetration schemes. Compared with the case of 10% penetration level, more energy and reserve is scheduled from wind farms for higher penetration levels. In addition, the amount of energy scheduled from conventional units is less when wind penetration is increased. The results suggest that the proposed model is beneficial for dealing with the large integration of wind, which is assumed to introduce more uncertainty to the operation of the system.

It is worth noting that the optimal choice for the flexible wind reserve margin policy factor depends on the wind generation forecast, as well as the operating conditions of the power system. Therefore, the policy factor is going to be different for different wind generation levels, load levels, and the system operation conditions. Various load parameters (e.g., hourly data, weekday and weekend data) as well as other system operational parameters (e.g., transmission congestion patterns) can be investigated to assort the policy factors based on wind generation levels and system operational conditions. These issues are further discussed in the next chapter.

The proposed flexible dispatch model seeks a balance between the operational costs and risk by allowing for flexible scheduling from wind power producers. Underestimating wind power allows the wind producer to ramp up when extra wind power production is available. Control mechanisms such as controlling the blade pitch would allow for adjusting the rotation speed and the generated power. Another simple way is to allow the wind production from the previously locked turbines. To elaborate, out of the entire wind farm turbines, a subset are producing power whereas the rest are locked and not producing even though they could. They can be unlocked and allowed to produce.

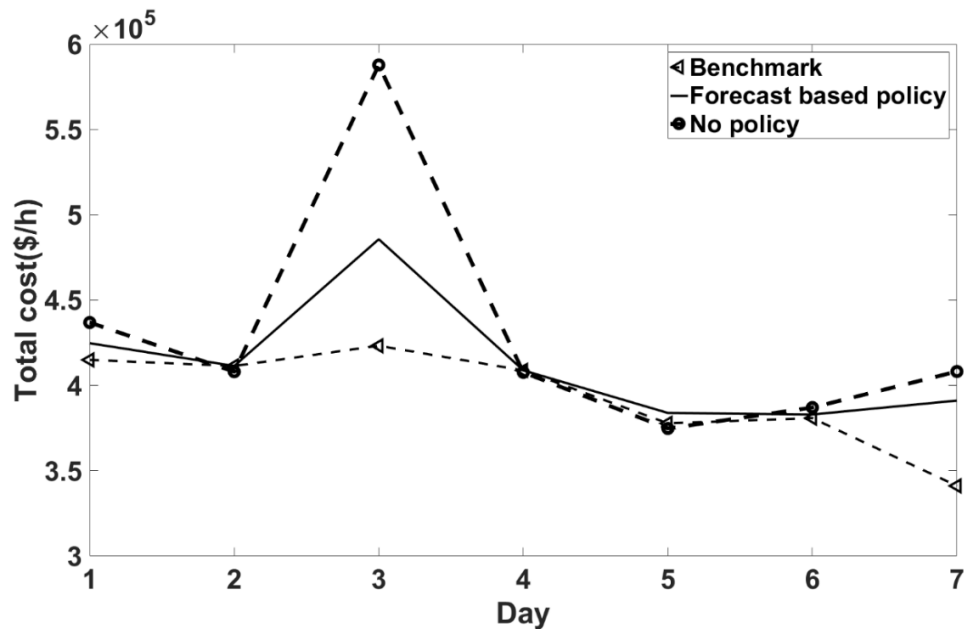


Fig. 3.9. Performance of the proposed policy determination vs. no policy and benchmark policy for a sample week in October.

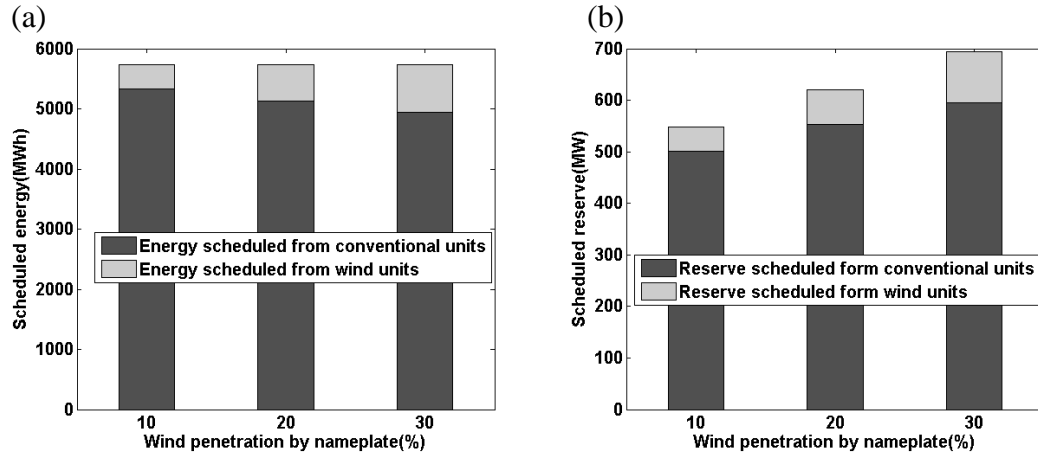


Fig. 3.10. (a) Scheduled energy vs. penetration level. (b) Scheduled reserve vs. penetration level.

In the proposed model, if the wind is underestimated and there is the ability to generate more and the system needs it, other turbines can be turned on as required by the system to provide reserve. If the system does not need the extra wind generation, wind curtailment is allowed, which would be performed by shutting down the extra wind turbines.

It is apparent that the optimal choice for the wind policy depends on the cost of curtailing load. In this study, the demand is considered perfectly inelastic and a fixed value of lost load (VOLL) has been applied to penalize the load shedding. However, if the demand is considered to be elastic, i.e., if demand response is taken into account, the risk costs can be reduced. Considering demand response can allow for larger wind reserve margin policy factors by introducing another degree of freedom in the proposed flexible dispatch.

3.5. Conclusions

Integration of large-scale wind generation in the power system increases the uncertainty that the operator has to deal with due to the variability of the wind energy. Today, renewables are not contributing sufficiently towards flexibility relative to the uncertainty that they are introducing. The small share of the renewable generators, allows the operators to

accommodate them in spite of their uncertainty, and extract flexibility from other resources to compensate for the corresponding uncertainty. However, such practices will no longer be feasible in future with higher penetration of renewable resources. Thus, it is expected that the renewables will be required to take part in providing flexibility and participate in the power system balancing tasks.

The predicted wind generation using forecasting methods may not be the amount that is reliable for the operation of the system. Utilizing the concept of flexible wind reserve margin allows the operator to allocate a discounted amount of wind for energy, leaving a reliability margin to hedge against uncertainty. The extra production of the wind farm can then be used for balancing purposes. In this dissertation, a joint hour-ahead energy and reserve scheduling framework is proposed. A finite-state Markov chain 10-minute-ahead wind power forecast model, based on spatio-temporal analysis, has been utilized to calculate the conditional probability distribution of the wind farm generation for each step. The presented framework is used to find the appropriate level for allocating wind based on the predicted output. Numerical studies, via the IEEE RTS-96 test system, demonstrate the significant benefits obtained by incorporating the flexible wind reserve margin using a Markov-chain-based forecast. The actual and forecasted wind generation data are used to analyze the effectiveness of the presented model. The results communicate that scheduling the flexible wind reserve margin will allow the operator to increase the reliability margin of the system while reducing the total cost. Discounting the scheduled generation from wind would improve the reliability through handling the uncertainty at an early stage. It also addresses the existing cost trade-off between scheduling generation from wind and the risk associated with wind farm uncertainty and improves the overall cost of supplying the

demand. The proposed structure can be effectively used to deal with the forecast errors and achieve a more secure system operation.

CHAPTER 4

OFFLINE OPTIMIZATION OF RESERVE POLICY FACTORS FOR SCHEDULING WIND ENERGY AND RESERVE

4.1. Introduction

The rapid growth of wind power as a low-cost emission-free generation resource has unveiled great benefits for the power system. Wind generation has, however, created new challenges for power system operations due to its variability and uncertainty. Wind generation is also reported to be negatively correlated with load in specific regions [56].

Flexibility requirements in a power system depend on the grid infrastructure, the existing generation mixture, and operating procedures. System planners usually use historical data of renewable generation and conventional units forced outage rates (FOR) to determine the effective load carrying capability (ELCC) of renewable generators. This process translates into assigning proper capacity credit to renewable generators in resource adequacy studies [57]. When studying the operational aspects, flexibility is usually described within the context of operating reserves, entailing the system to be able to balance out the deviations of the realized renewable generator output from its forecasted production. Authors of [58], for instance, characterized flexibility in terms of power capacity (MW), ramp rate (MW/min), and ramp duration (min). Reference [37] explored the level of different types of operating reserve that is induced by wind integration, providing a list of methods used in different power systems and key results from both operating practice and integration analysis. Prior study proposed a new approach based on robust optimization to determine security criteria in presence of renewable generation [59]. In [38], an overview of the current practices for estimating the optimal amount of operating reserves for systems with

high wind penetration was presented. These methods primarily use the statistical information to come up with rough deterministic rules for the quantity of reserve that needs to be acquired. On the other hand, a large number of studies focus on stochastic features of the wind generation. Such studies usually characterize the variability and try to handle it within a given reliability criteria. Previous studies [60]-[61] try to describe the variability by fitting the data to known probability density functions, using parametric distribution of such probability functions. A probability distribution would then enable dispatch of reserve to meet an acceptable risk level [62]. The non-parametric approach, on the other hand, makes no assumption about the empirical distribution. Non-parametric statistical representation estimates flexibility requirements more accurately as compared with standard probability distributions [68]. In this regard, stochastic programming has been increasingly utilized in wind integration studies in order to deal with the uncertainty. Authors of [69], for instance, proposed a two-stage stochastic framework for committing reserves in systems with large share of wind generation.

Wind generation uncertainty encourages system operators to apply stochastic approaches. Recent research works have proposed stochastic and robust scheduling models that consider the effect of uncertainty [63]-[67]. Such models are not scalable enough for large systems. Stochastic programming methods can be too time-consuming to obtain an efficient solution in real-time operations, which would make them impractical. For this reason, inefficient, but fast, deterministic approaches are preferred over efficient, but slow, stochastic ones. The challenge to implement stochastic programming is also due to the computational burden that virtual bidding is adding to market security constrained unit

commitment (SCUC) and security constrained economic dispatch (SCED) models by increasing the amount of active transmission constraints. Market pricing is also another barrier against the adoption of stochastic programming.

In real-world operational practices, the operating reserve is usually determined based on an ad-hoc deterministic rule. In existing market models, deterministic reserve proxy constraints are applied in SCUC and SCED. The basic $N-1$ criterion, for example, states that the scheduled reserve quantity should exceed the single largest contingency. Other deterministic rules describe the required reserve as a function of both load level and wind generation level. The 3+5 rule suggests that the reserve should not be less than 3% of predicted load plus 5% of predicted wind generation [70]. As another example, the California Independent System Operator (CAISO) describes its operating reserve requirement as: 5% demand met by hydro + 7% demand met by other sources + 100% interruptible imports or single largest contingency [71].

It is worth noting that these rules are operational-state independent except for acquiring reserves based on some fixed percentage of wind, hydro, or load level. This motivates developing improved deterministic policies to better exploit the flexibility of power systems in presence of operating condition uncertainty. Offline stochastic simulations can be used to generate such deterministic policies. Offline approaches eliminate real-time computational issues of stochastic programming.

This chapter aims to assess the benefit of such hybrid methods in dealing with uncertain operating conditions. In the previous chapter a framework was presented that enhanced the flexibility of the system by allowing the wind generators to leave a flexible reserve

margin [72]. The proper level of wind reserve margin can be determined using an optimization framework that tries to strike a balance between the operating costs and the risk associated with the mismanagement of wind generation.

The focus of the present chapter is on developing a structure that uses offline analysis to develop wind reserve margin policies, which can be employed in real-time operations. Such offline analysis allows for modeling a broader range of uncertainty, making it applicable when there are multiple sources of uncertainty, e.g., multiple wind farms.

With the advent of computing and data storage capabilities, utilities are going to be capable of handling extremely large data sets. These data sets, often called big data, are used to improve decision-making. The development of data mining techniques provides a promising solution to handle the mentioned challenge regarding running real-time stochastic programs.

Data mining approaches were applied in various domains of power system studies including dynamic security assessment [73]-[76], load forecasting [77]-[78] and wind generation prediction [79]-[82]. Learning schemes were proposed to leverage the power of data mining tools. In such schemes a knowledge base is, first, prepared through comprehensive offline studies, in which a number of forecasted operating states are used to create a set of training cases. Then, the knowledge base is used to create classification models that characterize the decision rules to determine policies. The decision rules are, finally, used to map the real-time measurements to the classifications of the system conditions for making operation decisions.

In this chapter, an optimization model serves as a hypothetical, ideal reference case to determine the dispatch and reserve policies. Given the large number of possible operating

conditions, in order to be able to use this approach, one needs to classify the operating conditions and find the optimal policy for each category. The wind flexible reserve margin is assumed to be a function of the generation and load conditions. The system operator can then use the near real-time measurements from the wind farm to choose a proper policy based on the classified operating conditions.

In this study, a procedure has been proposed for using stochastic methods as well as the wind forecasting models to come up with proper policies for deploying wind generation in power system. The objective is to investigate the possibility of utilizing offline mechanisms in order to come up with deterministic policies that can improve the reserve procuring procedure.

The main contributions of this chapter are summarized as follows:

1) A scalable real-time procedure is proposed to replace the scenario-based stochastic methods that quickly become intractable. The merits of the proposed method are twofold. First, the uncertainty is addressed by leveraging the scenario-based stochastic method in offline analysis. Second, the real-time procedure stays easy to implement by deploying deterministic policies resulted from offline studies.

2) A flexible reserve margin-based algorithm, based on the approach used in chapter 3, has been applied to generate offline policies for discounting wind generation and scheduling energy and reserve in presence of wind.

3) A testing method is derived to assess the performance of the policies obtained through the proposed training procedure for scheduling wind reserve margin.

4) The performance of the proposed policy training algorithm is compared with its counterparts without applying the trained policies. The results show that the training based

on the risk-aware scheduling can reduce the overall cost. Therefore, it is shown that the proposed structure allows for capturing the benefits of a stochastic scheduling without having to deal with a large set of scenarios in real-time.

The rest of the chapter is organized as follows. Section 4.2 explains the offline procedure for training policy factors, which replaces the direct modeling of scenarios from the stochastic formulation. Section 4.3 describes the outlines of the joint energy and reserve scheduling method based on flexible wind reserve margin. This method is performed to develop the policy for each member of the training base. Section 4.4 presents the algorithms applied to test the proposed method used for drawing policy factors and compares it to other existing methods. Section 4.5 reports numerical results. Finally, section 4.6 concludes and summarizes the potential for future work.

4.2. Training the Policy Factors (Offline Analysis)

As described in chapter 3, a flexible wind reserve margin policy is used, where the amount of the wind generation that the operator can utilize is expressed as a fraction of the forecasted wind generation. This fraction is referred to as the wind reserve margin policy factor throughout this dissertation.

The algorithm proposed in the previous chapter for developing such policy factors, solves a scenario-based stochastic dispatch and reserve scheduling problem based on the short-term wind farm generation forecast. The short-term 10-minute wind generation forecast based on the finite-state Markov chain model is used to develop a scenario tree for the wind generation in the next hour, i.e., for the next six time intervals of 10 minutes.

The resulted policy should tell the operator the level of wind farm generation that can be scheduled. It is assumed that the operator intends to perform the scheduling procedure

for the next hour based on a short-term wind forecast. The look-ahead dispatch allows for better planning of the resources, considering the ramp up and ramp down capabilities of the conventional generators. One challenge in performing this look-ahead dispatch is that the number of scenarios increases with the increase in the length of interval. Furthermore, if the system includes multiple wind farms, the total number of scenarios will increase rapidly. This means that running a stochastic optimization program would take a significant time and cannot be performed in real-time.

As mentioned in section 4.1, one way to overcome this challenge is to resort to offline simulations for training the dispatch model. The results can be classified based on the initial conditions. In real time, the operator can use the near real-time measurements to map the current conditions of the system to the classified set and select the proper policy based on the results of the offline procedures. Fig. 4.1 presents an overview of the offline and real-time procedures.

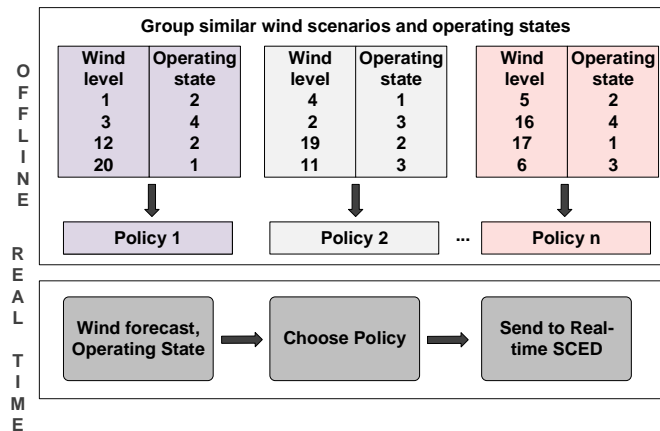


Fig. 4.1. The offline training and the real-time implementation procedures.

Note that the Markov chain wind forecast models that are used for this study are designed offline and their parameters, although different for different seasons and hours, are assumed to be constant. This allows us to train the flexible wind reserve margin policies

for various initial conditions in an offline manner, based on the constant parameters of the forecast model.

The forecast model outlines the spatial and temporal dynamics of the wind farm aggregate power output using data-driven analysis. Due to the non-stationary distributions of wind farm generation, the models (Markov chains) used to derive distributional forecasts, can have quite different parameters for different months and different epochs.

Therefore, forecast models are generated separately for each month and each epoch. Furthermore, when estimating the parameters of Markov chains, relevant historical data, i.e., the historical data from the same month and the same epoch, can be used. It is worth noting that the forecast Markov models can be updated, periodically, based on the new data.

Another operating condition that affects the reserve margin policy is the load condition. To take into account the diversity of load profiles and weather conditions, the calculations must be repeated for as many days as required to represent the modeled month/epoch. In the present study, the analysis has been performed for two load types (weekday and weekend).

Fig. 4.2 shows the training procedure for various time epochs and months; for each Markov model, 20 initial wind states have been trained and two different load levels have been considered. For each condition set, {month, epoch, load, wind state}, the policy factor is obtained using the two-phase method proposed in chapter 3. The outline of this two-phase method is briefly reviewed in the following section.

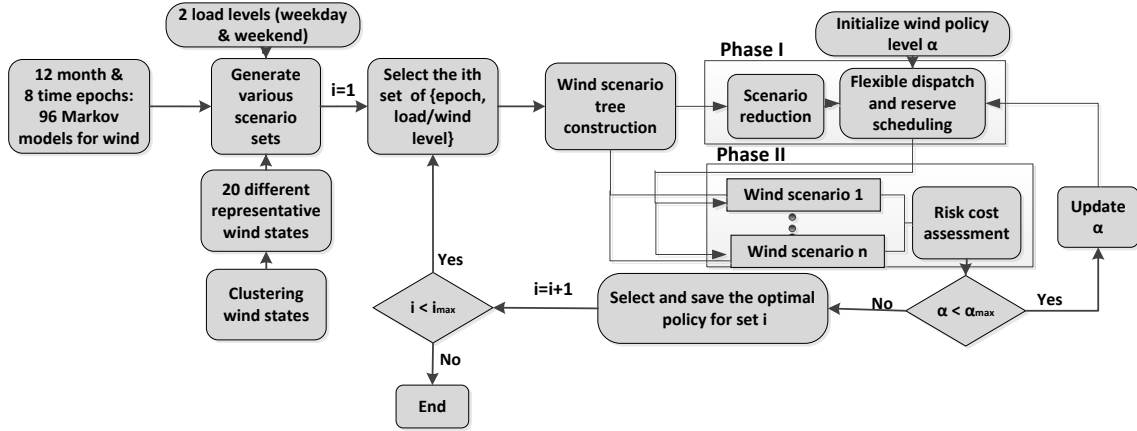


Fig. 4.2. Offline prediction-based policy training procedure.

In real-time, the actual wind power realization is compared to the trained initial wind levels and the nearest initial level is determined. Similarly, the nearest trained load level is determined. The policy obtained for that nearest wind level and the nearest load level is then implemented in the real-time model.

4.3. Outline of the Joint Energy and Reserve Scheduling

As described earlier in chapter 3, the approach for finding the best policy has been formulated in two phases. In the first phase, a scenario-based stochastic dispatch and reserve scheduling problem is solved based on the short-term wind farm generation forecast. This problem uses a reduced set of scenarios and its goal is to find the appropriate energy and reserve that can be scheduled from the wind farm to minimize the total cost. The total cost consists of the operational cost associated with procuring energy and reserve as well as the expected costs associated with inadequate reserve allocation. The first phase problem is shown by (4.1)-(4.26):

$$\begin{aligned} \text{Min} \quad & \sum_{g,t}(C_g^e p_{gt} + C_g^{rc} r_{gt}) + \sum_{w,t}(C_w^e p_{wt} + C_w^{rc} r_{wt}) + \sum_{s,t} \pi_s \{ \sum_n C_c^n (ls_{nst}^+ + \\ & ls_{nst}^-) + \sum_w (C_p + C_w^{re}) p_{wst}^{penalty} + \sum_g (C_g^{re} r_{gst}) + \sum_w (C_w^{re} r_{wst}) + \sum_w (C_w^{rc} \Delta_{wst}) \} \end{aligned} \quad (4.1)$$

Subject to:

Base case constraints:

$$p_g^{min} \bar{u}_{gt} \leq p_{gt}, \forall g, t \quad (4.2)$$

$$p_{gt} + r_{gt} \leq P_g^{max} \bar{U}_{gt}, \forall g, t \quad (4.3)$$

$$0 \leq r_{gt} \leq R_g^{10} \bar{U}_{gt}, \forall g, t \quad (4.4)$$

$$\sum_{g \in G} r_{gt} \geq p_{gt} + r_{gt} + \sum_w \xi_{wt}, \forall g, t \quad (4.5)$$

$$\xi_{wt} \geq p_{wt} - (P_{wt}^f - \beta \sigma_{wt}), \forall w, t \quad (4.6)$$

$$p_{gt} - p_{g,t-1} \leq R_g^{10}, \forall g, t, \bar{U}_{gt} = 1, \bar{U}_{g,t-1} = 1 \quad (4.7)$$

$$p_{g,t-1} - p_{gt} \leq R_g^{10}, \forall g, t, \bar{U}_{g,t-1} = 1, \bar{U}_{gt} = 1 \quad (4.8)$$

$$p_{wt} + r_{wt} \leq \alpha P_{wt}^f, \forall w, t \quad (4.9)$$

$$p_{kt} - B_k(\theta_{nt} - \theta_{mt}) = 0, \forall k, t \quad (4.10)$$

$$-P_k^{max} \leq p_{kt} \leq P_k^{max}, \forall k, t \quad (4.11)$$

$$\sum_{g \in g(n)} p_{gt} + \sum_{k \in \delta^+(n)} p_{kt} - \sum_{k \in \delta^-(n)} p_{kt} + \sum_{w \in w(n)} p_{wt} = d_{nt}, \forall n, t \quad (4.12)$$

$$p_{wt}, r_{wt} \geq 0, \forall w, t \quad (4.13)$$

Second-stage constraints:

$$p_{kst} - B_k(\theta_{nst} - \theta_{mst}) = 0, \forall k, t \quad (4.14)$$

$$-P_k^{max} \leq p_{kst} \leq P_k^{max}, \forall k, t \quad (4.15)$$

$$\begin{aligned} & \sum_{g \in g(n)} (p_{gt} + r_{gst}) + \sum_{k \in \delta^+(n)} p_{kst} - \sum_{k \in \delta^-(n)} p_{kst} + \sum_{w \in w(n)} (p_{wt} + r_{wst}) + \\ & ls_{nst}^+ - ls_{nst}^- = d_{nt}, \forall n, s, t \end{aligned} \quad (4.16)$$

$$r_{gst} \leq r_{gt}, \forall g, s, t \quad (4.17)$$

$$-r_{gst} \leq r_{gt}, \forall g, s, t \quad (4.18)$$

$$p_g^{min} \leq p_{gt} + r_{gst} \leq p_g^{max}, \forall g, s, t \quad (4.19)$$

$$RR_{gst} = r_{gt} - r_{gst}, \forall g, s, t \quad (4.20)$$

$$-r_{wst} \leq r_{wt} + p_{wst}^{penalty}, \forall g, s, t \quad (4.21)$$

$$0 \leq p_{wt} + r_{wst}, \forall w, s, t \quad (4.22)$$

$$p_{wt} + r_{wst} + rr_{wst} \leq W_{wst}, \forall w, s, t \quad (4.23)$$

$$\Delta_{wst} \geq r_{wst} + rr_{wst} - r_{wt}, \forall w, s, t \quad (4.24)$$

$$\sum_{g \in g(n)} rr_{gst} + \sum_{w \in w(n)} rr_{wst} \geq p_{gt} + r_{gt}, \forall g, w, s, t \quad (4.25)$$

$$rr_{wst}, \Delta_{wst}, ls_{nst}^+, ls_{nst}^-, p_{wts}^{penalty} \geq 0, \forall w, n, s, t. \quad (4.26)$$

Note that the objective function allows bidding for reserve; some markets do not allow participants to submit bids for reserve in real-time markets. The chosen model allows for bidding of reserve to better reflect potential lost opportunity costs by generators but the model can be easily modified to remove such bidding if desired. Such minor changes do not affect the primary findings and conclusions.

The solution of this first phase determines the dispatch and reserve decisions, p_{gt} , r_{gt} , p_{wt} , and r_{wt} . The optimal values of these variables are then fed as inputs to the risk analysis problem in the second phase. In this phase, a deterministic model is used to test the first phase decisions against every possible scenario. This phase aims to model the uncertainty that has not been modeled in the first phase in the reduced set of scenarios.

Please note that the result of the first phase is not the true optimal value (extensive scenario-based stochastic model). This requires us to ensure the stability of the scenario-

based stochastic program, which is solved using the reduced set of scenarios. The stability of a stochastic program can be stated in form of in-sample and out-of-sample requirements [83]. Here, the results of the stochastic programming on the reduced set of scenarios is tested against all the scenarios to ensure out-of-sample stability. Given the first phase decisions for energy and reserve schedule, the second phase tries to minimize the realized costs associated with each possible scenario:

$$\begin{aligned} \text{Min} \quad & \sum_t (\sum_g (C_g^{re} r_{gst}) + \sum_w (C_w^{re} r_{wst}) + \sum_w (C_w^{rc} \Delta_{wst}) + \sum_w (C_p + C_w^{re}) p_{wst}^{penalty} + \\ & \sum_n C_c^n (ls_{nst}^+ + ls_{nst}^-)) \end{aligned} \quad (4.27)$$

Subject to: constraints (4.14)-(4.26).

To find the best policy, the two-phase procedure is performed repetitively for various factors. Initially, a certain fraction of the predicted wind generation is assumed to be utilizable. Beginning with this small value for α , a stochastic program is solved using the reduced set of scenarios in the first phase. The obtained solution gives the optimum schedule as well as the operational cost for that specific value of α . In the second phase, a risk analysis model is run to come up with the average risk cost associated with that scheduling policy.

The overall problem can be described in the following simplified form:

$$\text{Min}_{\alpha} \text{ scheduling cost}(\alpha) + \sum_s \text{risk cost}_s(p_{gt}^*, r_{gt}^*, p_{wt}^*, r_{wt}^*) \quad (4.28)$$

Subject to:

$$(p_{gt}^*, r_{gt}^*, p_{wt}^*, r_{wt}^*) \in \underset{(p_{gt}, r_{gt}, p_{wt}, r_{wt})}{arg \min} \text{ scheduling cost}(\alpha) \quad (4.29)$$

In order to obtain an approximate solution to this problem, the value of α is varied. The described procedure is repeated for various α values and the optimum operational and

risk cost associated to each policy is recorded. The policy that has the minimum sum of the scheduling cost and the risk cost is expected to be the least-cost policy for scheduling energy and reserve from wind.

4.4. Real-time Implementation of Policies

In this section, the real-time implementation and the method applied for testing the behavior of the policies derived for wind reserve margin is described. This section describes the real-time implementation of proposed policy, i.e. the prediction-based policy, as well as two other ad-hoc policies. The real-time structure of the proposed prediction-based policy is explained in section 4.4.1. The next policy, which will be described in section 4.4.2, makes use of the forecasted distribution to schedule a certain percentile of the forecasted generation. The third policy, which is described in section 4.4.3, is a fixed policy that utilizes a fixed fraction of the forecasted mean. Section 4.4.4 introduces the base case where no policy is used. Section 4.4.5 develops a structure for analyzing the performance of the described policies. Specifically, a risk analysis structure is proposed to test the real-time implementations.

4.4.1. Prediction-based Policy

In order to evaluate the results of the proposed training method, one should examine the policy derived by the offline procedure against a large set of scenarios. The testing procedure should be first, compatible with the way the policy has been determined and second, be performed for the same set of uncertainty as assumed at the first-stage. Note that the online implementation tool does not perform the risk analysis phase, i.e., it deploys

the generated policy into the first phase problem to determine the energy and reserve schedule $(p_{gt}, r_{gt}, p_{wt}, r_{wt})$. The real-time procedure implemented in the current study is, thus, as follows:

Assume that the policies have been obtained for a number of condition sets, {month, epoch, load profile, wind state}, using the stochastic optimization model. For different initial wind states in any epoch, choose the policy $\bar{\alpha}$ based on the one developed for the nearest load and wind state. Put the policy in the optimization described below and solve the stochastic process for the reduced set of scenarios. Fig. 4.3 shows the flowchart for this procedure.

$$\begin{aligned} \text{Min} \quad & \sum_{g,t}(C_g^e p_{gt} + C_g^{rc} r_{gt}) + \sum_{w,t}(C_w^e p_{wt} + C_w^{rc} r_{wt}) + \sum_{s,t} \pi_s \{ \sum_n C_c^n (ls_{nst}^+ + \\ & ls_{nst}^-) + \sum_w (C_p + C_w^{re}) p_{wst}^{penalty} + \sum_g (C_g^{re} r_{gst}) + \sum_w (C_w^{re} r_{wst}) + \sum_w (C_w^{rc} \Delta_{wst}) \} \end{aligned} \quad (4.1)$$

Subject to: constraints (4.2)-(4.8), constraints (4.10)-(4.26),

$$p_{wt} + r_{wt} \leq \bar{\alpha} P_{wt}^f, \forall w, t. \quad (4.30)$$

In order to evaluate the performance of this policy, the results of this problem $(p_{gt}, r_{gt}, p_{wt}, r_{wt})$ can be sent to a risk analysis program. This risk analysis is described in section 4.4.4.

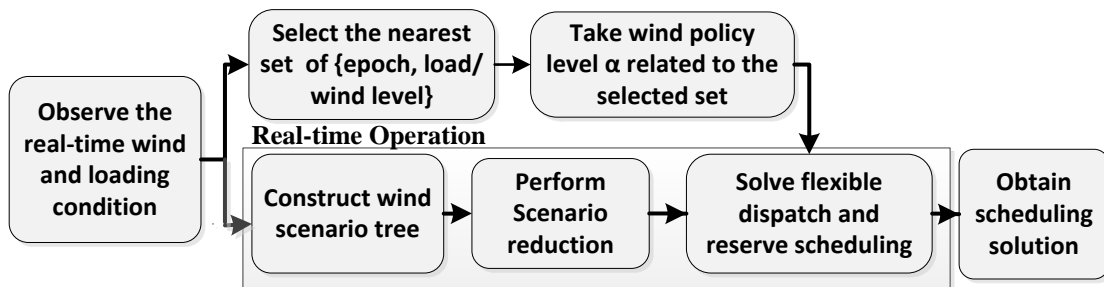


Fig. 4.3. Real-time implementation procedure of the proposed policy.

4.4.2. Probability Distribution Percentile-based Policy

In this approach a probabilistic metric (90% percentile of the cumulative distribution of predicted wind) has been used. Fig. 4.4 displays the procedure. This percentile is applied instead of the policy factor in the original two-stage stochastic process for a reduced set of scenarios to allow for comparison with the proposed approach:

$$\begin{aligned} \text{Min} \quad & \sum_{g,t}(C_g^e p_{gt} + C_g^{rc} r_{gt}) + \sum_{w,t}(C_w^e p_{wt} + C_w^{rc} r_{wt}) + \sum_{s,t} \pi_s \{ \sum_n C_c^n (ls_{nst}^+ + \\ & ls_{nst}^-) + \sum_w (C_p + C_w^{re}) p_{wst}^{penalty} + \sum_g (C_g^{re} r_{gst}) + \sum_w (C_w^{re} r_{wst}) + \sum_w (C_w^{rc} \Delta_{wst}) \} \end{aligned} \quad (4.1)$$

Subject to: constraints (4.2)-(4.8), constraints (4.10)-(4.26),

$$p_{wt} + r_{wt} \leq per_{wt}^f, \forall w, t. \quad (4.31)$$

4.4.3. Fixed Policy

The fixed policy assumes a fixed value for policy factor α , regardless of the value of input for wind generation. This fixed policy is put in the original two-stage problem formulation as shown below:

$$\begin{aligned} \text{Min} \quad & \sum_{g,t}(C_g^e p_{gt} + C_g^{rc} r_{gt}) + \sum_{w,t}(C_w^e p_{wt} + C_w^{rc} r_{wt}) + \sum_{s,t} \pi_s \{ \sum_n C_c^n (ls_{nst}^+ + \\ & ls_{nst}^-) + \sum_w (C_p + C_w^{re}) p_{wst}^{penalty} + \sum_g (C_g^{re} r_{gst}) + \sum_w (C_w^{re} r_{wst}) + \sum_w (C_w^{rc} \Delta_{wst}) \} \end{aligned} \quad (4.1)$$

Subject to: constraints (4.2)-(4.8), constraints (4.10)-(4.26),

$$p_{wt} + r_{wt} \leq \bar{\alpha} P_{wt}^f, \forall w, t. \quad (4.32)$$

In this study, $\bar{\alpha}$ for the deterministic approach is assumed to be equal to 90%.

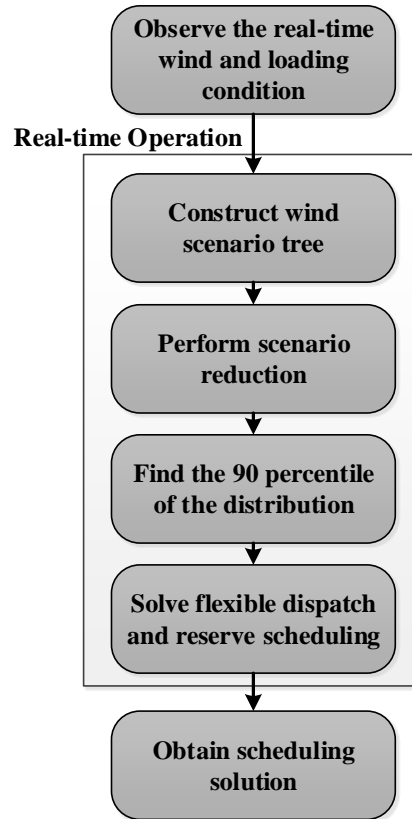


Fig. 4.4. Real-time implementation procedure of the Probability distribution-based policy.

4.4.4. Base Case

The base case is when no policy is employed, meaning that the operator doesn't discount the wind, or $\bar{\alpha} = 1$.

4.4.5. Performance Analysis Structure

A risk analysis program, similar to the one described in (4.27), can be used to evaluate the performance of the different policies. Fig. 4.5 shows the risk evaluation procedure used for testing the results of the described policies. The next section presents the numerical test results, performed on a test system, for the three policies described in sections 4.4.1, 4.4.2 and 4.4.3.

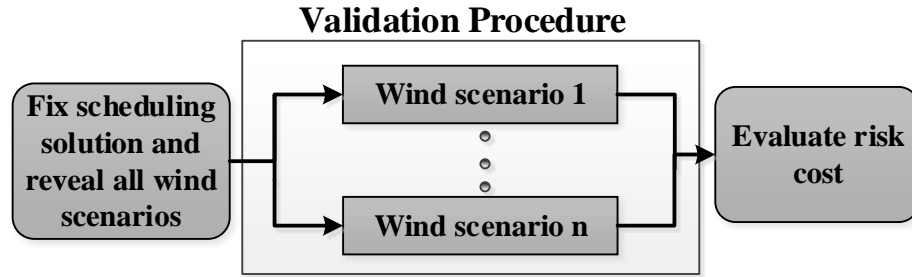


Fig. 4.5. Testing procedure based on risk evaluation.

4.5. Numerical Results

4.5.1. The Single Wind Farm Case

As mentioned before, the major limitation in a stochastic model is that modeling all the scenarios is not time efficient. If the number of scenarios is large, modeling all scenarios can make the problem intractable, especially, in a large system. Usually, a reduced set of scenarios is used instead. In this section the three different policies, which were proposed in section 4.4, are tested. Note that all the three approaches described have a similar structure. First, a stochastic problem is solved for a reduced set of scenarios. To evaluate the performance, the energy and reserve schedule is then sent to a risk analysis stage that runs for all possible scenarios. To create a comparison benchmark, two more test structures are developed. The studies have been performed in a deterministic structure and for a large set of scenarios, as well. The three proposed algorithms have been performed for the deterministic case (1 scenario), the reduced set (5 scenarios) and a large set of scenarios (100 scenarios). These nine algorithms are summarized in Table 4.1, where their name, their decision making technique and their scenario modeling approaches are shown.

The proposed structure has been applied to the IEEE RTS-96 test system [84]. The test system is modified by integrating a 1500 MW wind farm, at bus 40, which accounts for roughly 30% of the total system-wide generation capacity. The wind generation data of a wind farm for the year 2010 [26] is used after proper scaling to suit the chosen wind farm capacity. For the current simulation, the finite-state Markov model of the spatio-temporal analysis for the 9 AM-12 AM epoch is used.

Table 4.1. Policy generation algorithms classification

PB_D	Prediction-based policy	Deterministic
PB_RS	Prediction-based policy	Reduced set of scenarios
PB_LS	Prediction-based policy	Large set of scenarios
DPB-D	Distribution percentile-based policy	Deterministic
DPB-RS	Distribution percentile-based policy	Reduced set of scenarios
DPB-LS	Distribution percentile-based policy	Large set of scenarios
F-D	Fixed policy	Deterministic
F-RS	Fixed policy	Reduced set of scenarios
F-LS	Fixed policy	Large set of scenarios

The load classification used in this study is based on data from IEEE RTS-96 system [84]. In the dataset, the daily load profiles are given for specific seasons and day types. In real-world case, having the real load data, the daily profiles could be clustered into classes to form different day types and seasons that may not actually correspond to a real season or day type.

In the current study, the attention has been focused on one month to be able to model more initial states. All simulation results presented are for month April, henceforth. All scenario reductions are performed using the procedure introduced in [53], which reduces the scenarios to their best approximation based on the Kantorovich distance of probability distributions. The algorithm eliminates one scenario at a time until the desired number of

scenarios is achieved. For each initial wind level, the risk analysis phase has been run for all the possible scenarios created by the Markov chain forecast model. The results are expressed in terms of average scheduling and risk cost.

In order to analyze the performance of the above methods, a set of base case studies with no policies have been run where the operator counts on the wind predicted mean (in other words, $\bar{\alpha} = 1$) for three different problem structures. The first one, which is referred to as the benchmark case, is a deterministic version of the scheduling problem, the second one models a reduced set of scenarios, and the third one models a large set of scenarios.

Note that all tested methods have the same foresight regarding wind forecast and none of them is shortsighted. This ensures that the difference in the presented results reflect the difference in the applied policy.

Table 4.2 presents the average scheduling and total cost for each initial wind condition for the case with reduced set of scenarios. The results are for multiple initial levels, which accounts for various penetration levels up to 30% penetration level by nameplate. The number of scenarios that encountered load shedding in the testing stage is listed for each test level. The results are for a one-hour period. The cost improvement beyond the benchmark case is also presented.

Table 4.2. Comparison between the fixed, distribution percentile-based and prediction-based approaches (reduced set of scenarios)

Policy	Wind level (%)	Scheduling cost (\$/h)	Total cost (\$/h)	Number of scenarios with load shedding	Improvement in total cost (%)	EENS (MWh)	LOLP
F-RS	3	270325.9	273860.1	0	8.7	0	0
F-RS	6	261300.6	263067.6	0	6.26	0	0
F-RS	9	253163.1	258297.0	0	13.46	0	0
F-RS	12	247146.7	253124.4	0	11.04	0	0
F-RS	15	229262.3	235805.9	2	13.98	1.33E-08	6.29E-04
F-RS	18	222984.5	226252.8	2	18.04	1.30E-08	5.69E-04
F-RS	21	212396.8	220599.6	0	17.07	0	0
F-RS	24	204860.3	214388.1	5	24.06	4.70E-08	2.49E-03
F-RS	27	196204.7	220114.5	20	32.20	2.02E-05	1.54E-02
DPB-RS	3	270664.7	273851.1	0	8.7	0	0
DPB-RS	6	261438.8	265869.5	0	5.3	0	0
DPB-RS	9	253146.6	258553.7	0	13.4	0	0
DPB-RS	12	248045.4	255352.4	0	10.3	0	0
DPB-RS	15	228880.6	237527.1	10	13.4	3.35E-08	2.72E-03
DPB-RS	18	221784.0	227265.4	2	17.7	1.30E-08	5.69E-04
DPB-RS	21	211848.1	223870.1	0	15.8	0	0
DPB-RS	24	204950.6	216958.1	6	23.1	2.28E-07	1.63E-02
DPB-RS	27	194758.9	232768.2	35	28.3	3.07E-05	2.58E-02
PB-RS	3	270416.4	273866.0	0	8.70	0	0
PB-RS	6	262086.1	262691.4	0	6.39	0	0
PB-RS	9	254357.7	257999.9	0	13.56	0	0
PB-RS	12	247146.7	253124.4	0	11.04	0	0
PB-RS	15	229262.3	235805.9	2	13.98	1.33E-08	6.29E-04
PB-RS	18	222984.5	226252.8	2	18.04	1.30E-08	5.69E-04
PB-RS	21	212396.8	220599.6	0	17.07	0	0
PB-RS	24	207533.9	211699.2	0	25.01	0	0
PB-RS	27	200085.1	212229.5	14	34.63	1.11E-05	1.20E-02

The results show that the prediction-based policy has a lower total cost in almost all the studied wind penetration levels. It also has a significantly less number of the scenarios where load shedding occurs.

Table 4.3 shows the results when the same procedure is deployed, with the exception that the first phase stochastic optimization is performed for a large number of scenarios.

Table 4.3. Comparison between the fixed, distribution percentile-based and prediction-based approaches (large set of scenarios)

Policy	Wind level (%)	Scheduling cost (\$/h)	Average risk cost (\$/h)	Total cost (\$/h)	Number of scenarios with load shedding	Improvement in total cost (%)
F-LS	3	268259.6	5794.6	274054.3	0	8.64
F-LS	6	263562.4	45.3	263607.7	0	6.07
F-LS	9	259114.8	52.1	259166.9	0	13.17
F-LS	12	255547.2	36.3	255583.6	0	10.17
F-LS	15	240800.2	89.6	240889.9	0	12.13
F-LS	18	231853.5	36.5	231890.1	0	16.00
F-LS	21	216857.9	2672.65	219530.6	0	17.48
F-LS	24	217293.2	63.3	217356.5	0	23.01
F-LS	27	203945.1	908.9	204854.1	0	36.90
DPB-LS	3	268991.1	5671.7	274662.8	0	8.43
DPB-LS	6	268469.2	5779.6	274248.8	0	2.27
DPB-LS	9	263146.6	5407.1	268553.7	0	10.03
DPB-LS	12	256810.8	8.7	256819.5	0	9.74
DPB-LS	15	241307.2	32.5	241339.7	0	11.96
DPB-LS	18	232724.2	14.1	232738.3	0	15.69
DPB-LS	21	217301.1	2667.5	219968.6	0	17.31
DPB-LS	24	218826	4.0	218830.0	0	22.48
DPB-LS	27	205511.8	720.6	206232.4	0	36.48
PB-LS	3	268130.7	5954.8	274085.5	0	8.63
PB-LS	6	263527.1	57.4	263584.5	0	6.07
PB-LS	9	259114.8	52.1	259166.9	0	13.17
PB-LS	12	255547.2	36.4	255583.6	0	10.17
PB-LS	15	240273.1	170.1	240443.2	0	12.29
PB-LS	18	231813.6	41.4	231855	0	16.01
PB-LS	21	216070.5	2905.9	218976.4	0	17.68
PB-LS	24	217293.2	63.3	217356.5	0	23.01
PB-LS	27	203099.9	980.2	204080.1	0	37.14

The results show that the proposed stochastic approach performs better when more scenarios are modeled. As expected, the number of scenarios that lead to load shedding is decreased when a larger number of scenarios are modeled since modeling a larger number of scenarios in the first phase will leave less space for uncertainties to perturb the results. The simple fixed policy also performs well in comparison to the distribution percentile based policy. This serve as a reference that some very simple reserve rules can perform adequately if chosen based on the historical trends.

Please note that this deterministic policy (here, 0.9) has not been chosen based on extensive analysis. In other words, having chosen another deterministic policy could lead to

better or worse results. This may be an indication that solving the problem for a simple uncertainty set for wind generation may ease the computation burden of stochastic analysis, especially, when drastic wind ramps are not modeled. The investigation of the performance of such uncertainty sets is left for future work.

All simulations are performed using the Gurobi solver in AMPL environment on an Intel (R) Core (TM)2 Duo CPU @3.16 GHz computer with 4 GB of memory. The average solution time of the offline model including the scheduling phase and the risk analysis phase for each specific alpha was about 124 seconds. The average solution times of the online hour-ahead model for the proposed algorithms are reported in Table 4.4.

The SCED problem has 4404 variables and has 6378 constraints for the deterministic model. These numbers are increased to 15732 variables and 20562 constraints in a two-stage stochastic program with a small set of scenarios. The two-stage stochastic program with a large set of scenarios had 285996 variables and 363464 constraints.

Table 4.4. Average solution times for the tested policies

Policy	Average solution time (S)	Policy	Average solution time (S)
F –RS	1.39	F –LS	82.30
DPB –RS	1.46	DPB –LS	80.21
PB-RS	1.36	PB-LS	75.31

In order to show the performance of the proposed method in alleviating the need for modeling all scenarios, the cost savings of the PB-RS approach, with respect to the benchmark are presented in Table 4.5. The second column shows the maximum potential cost

savings by switching from a determinist structure (benchmark case) to a stochastic structure with a large set of scenarios. The last column shows what portion of the potential cost savings is captured by the proposed policy in a reduced scenario case.

To elaborate, this ratio is given by

$$Cost\ saving\ ratio = \frac{c_{base\ case,D} - c_{PB,RS}}{c_{base\ case,D} - c_{base\ case,LS}} \quad (4.34)$$

where, $c_{base\ case,D}$ is the cost for the base case in a deterministic structure, $c_{base\ case-LS}$ is the cost for the base case when a large number of scenarios are modeled, and $c_{PB,RS}$ is the cost for the prediction-based method when a reduced number of scenarios are modeled. The results corroborate that the prediction-based method is capable of capturing the same cost savings while modeling fewer scenarios.

Table 4.5. Cost savings captured in the prediction-based method

Wind level (%)	Cost savings in PB-RS (\$/h)	Potential cost savings (\$/h)	Ratio
3	26098.7	25910.6	1.01
6	17941.5	17048.3	1.05
9	40482.6	39313.8	1.03
12	31409.8	28950.7	1.08
15	38331.8	33641.6	1.14
18	49807.0	44204.8	1.13
21	45418.7	47046.9	0.97
24	70601.6	64944.3	1.09
27	112433.8	120455.2	0.93

Fig. 4.6 shows the total cost for different wind levels, in comparison to the benchmark and the base case with a large set of scenarios, for two different cases. The first case is where the obtained policy, from the prediction-based method, is used in a deterministic structure. The second one is where the obtained policy is used in a stochastic structure with

a reduced number of scenarios. As can be seen, the policy obtained from the prediction-based method performs closely to the base case modeling a large set of scenarios, both in a deterministic and a reduced stochastic structure.

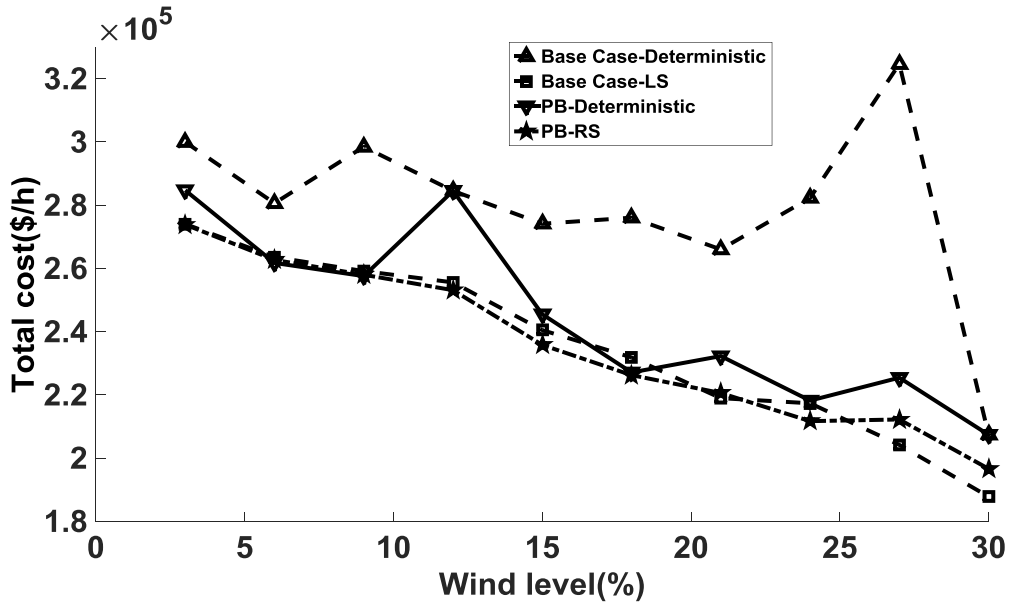


Fig. 4.6. Total cost for the proposed prediction-based method compared to the base case. PB: prediction-based policy, RS: reduced set of scenarios, LS: large set of scenarios.

The general message of this graph is that the deterministic case that models only one scenario has a higher total cost. The cost for wind level around 27% is a bit higher than the neighbor penetration levels and this is true for almost all modeled methods. Note that the cost for different penetration levels need not follow a smooth trend since for each initial level of wind we are finding the closest among the trained initial values and depending on how far is the realized initial value from the trained initial value, the error would be different.

4.5.2. Multiple Wind Farms

An extension for the problem is the case where there are multiple wind farms in the system. Discounting the generation from multiple wind farms would be more challenging in such situations. One important aspect when considering multiple wind farms is the fact that a large set of scenarios should be modeled. The need for modeling larger number of scenarios in a multi-wind farm system can be alleviated by taking advantage of offline analysis.

Nearby wind farms are exposed to similar weather variation patterns. Therefore, the power outputs of different wind farms in a system are both temporally and spatially correlated. The correlation of the output of two wind farms is in fact a measure of the synchronism in their output variations. The discounting for wind can be implemented in a way that takes the impact of correlation of multiple wind farms into consideration. This correlated structure of the data for wind farms can be exploited to develop policies that better model the realization of the incoming wind generation.

In this section, the historical data from a set of wind farms has been used to capture the correlated structure of their generation output in coming up with reserve margin policy for multiple wind farms. The real wind measurements in three locations based on the Australian windfarm dataset is used. A vector quantization technique [85] has been used for modeling the probability density functions using the distribution of typical vectors. The joint empirical distribution of the wind farms outputs has been derived based on historical data. The vector quantization is performed based on the K-means clustering algorithm to find the groupings in the dataset and identify the joint typical occurrences for multiple wind

farms. The results of the vector quantization are then used to model only the typical scenarios in the risk analysis phase of the policy generation procedure.

In this section, the proposed policy has been performed for two more test systems, one with two wind farms and one with three wind farms. For the two wind farm case, the same test system is modified by integrating two 750 MW wind farms, at buses 22 and 40, accounting for roughly 30% of the total system-wide generation capacity. For the three wind farm case, the system is modified by integrating three 500 MW wind farms, at buses 22 and 40 and 68. The results are shown in Table 4.6 and Table 4.7, respectively. The results confirm that the proposed reserve policy outperforms traditional techniques by capturing the majority of the potential savings.

Table 4.6. Comparison between the fixed and prediction-based approaches for two wind farms

Policy	Wind level (%)	Average risk cost(\$/h)	Total cost(k\$/h)	Captured percentage of potential cost savings (%)
F-RS	6	511.2	275.2	51
F-RS	12	361.1	269.8	43
F-RS	15	639.6	267.4	57
F-RS	18	436.8	264.2	69
F-RS	21	0.8	259.7	58
F-RS	24	0.1	259.1	50
F-RS	27	0.0	254.2	57
F-RS	30	0.0	249.8	0
PB-RS	6	551.5	275.0	82
PB-RS	12	401.1	269.6	67
PB-RS	15	666.7	267.2	81
PB-RS	18	585.5	264.1	74
PB-RS	21	1.2	259.5	76
PB-RS	24	0.0	258.4	85
PB-RS	27	0.0	254.0	70
PB-RS	30	0.0	249.8	0

Table 4.7. Comparison between the fixed and prediction-based approaches for three wind farms

Policy	Wind level (%)	Average risk cost(\$/h)	Total cost(k\$/h)	Captured percentage of potential cost savings (%)
F-RS	6	72	257.3	40
F-RS	12	234	248.4	20
F-RS	15	142	240.37	80
F-RS	18	144	225.3	0.1
F-RS	21	182	215.7	10
F-RS	24	175	205.7	10
F-RS	27	214	194.4	10
F-RS	30	142	256.5	70
PB-RS	6	234	248.4	20
PB-RS	12	775	237.2	90
PB-RS	15	651	223.3	70
PB-RS	18	412	213.6	60
PB-RS	21	1170	201.4	50
PB-RS	24	214	194.4	10
PB-RS	27	72	257.3	40
PB-RS	30	234	248.4	20

4.6. Conclusions

In this chapter, the benefits of the prediction-based policy training methods have been investigated. A flexible reserve margin based algorithm has been applied to train offline policies for discounting wind generation and scheduling energy and reserve in presence of wind. A scenario-based stochastic programming approach is leveraged to capture the effect of various possible wind scenarios based on short-term wind forecast.

A testing method is derived to assess the performance of the policies obtained through the proposed training procedure for scheduling wind reserve margin. The performance of the proposed policy training algorithm is compared with its counterparts without applying

the trained policies. The results corroborate that the training based on the risk-aware scheduling can reduce the overall cost, while not imposing the burden of stochastic programming in real-time operation.

Numerical studies, via the IEEE RTS-96 test system, demonstrate the benefits of the proposed structure.

CHAPTER 5

MARKET IMPLICATIONS OF WIND RESERVE MARGIN

5.1. Introduction

This chapter examines the market implications of the wind reserve margin policies used to mitigate uncertainty from wind resources. In the previous chapter, a training structure was developed, which uses offline stochastic analysis to come up with deterministic rules for scheduling wind reserve margins. Reserve margins offer more flexibility for the system operation. Renewables can provide cheaper reserves, which have a lower quality of service, in comparison to reserves from conventional generators. It is worth noting that since renewables have uncertain outputs, reserves from such resources should be treated as stochastic reserves.

As an enhancement to the existing deterministic procedures, stochastic models can be used offline to derive deterministic operation policies, as described in the previous chapter. Such an offline approach eliminates real-time computational burden and market pricing issues while accounting for uncertainty in the operating conditions of the system.

This chapter investigates the market implications of deploying the deterministic reserve margin policies. Analyzing the impacts of implementing new policies on the outputs of the electricity markets is an established way of determining the benefits of such new market policies [86]-[89]. In this dissertation, the proposed approach is compared with a base case deterministic approach that does not use reserve margin policies. The marginal costs and ancillary services bids of generators are modeled. In addition, a market settlement scheme is proposed that can be used for the policy proposed. In the proposed structure, the

generators are compensated for the energy and reserve that they provide. The reserve providers are compensated for both the reserve capacity and the reserve activation. The reserve activation payments are dependent upon the performance of the reserve resource for various realization scenarios. The following sections will discuss the formulation of these models and the results.

5.2. Reserve Policy Factor Determination

The off-line training methodology is used for determining the policy factor for scheduling energy and reserve from wind generation. The offline analysis determines the policy factor for a variety of operating conditions, which are described in terms of the initial wind levels and the initial load levels [90].

In real-time, the actual wind power realization is compared to the trained initial wind levels and the nearest initial level is determined. Similarly, the nearest trained load level is determined. The policy obtained for that nearest wind level and the nearest load level is then implemented in the real-time model.

5.3. Implementation of the SCED Using Reserve Policy Factors

The model has been modified to enable calculating payments to different parties. In this model, the energy schedule remains fixed and reserve schedule is discounted by α . To ensure consistency with the existing market structures, the SCED implementation has been kept simple by solving a deterministic problem.

The offline stochastic structure has been exploited to select a policy factor that can be passed into a deterministic scheduling framework. Energy schedule is fixed and the part of the production, which was spared for reserve, is discounted.

The SCED implementation is formulated as given below:

$$\text{Min } \sum_{g,t} (C_g^e p_{gt} + C_g^{rc} r_{gt}) + \sum_{w,t} (C_w^e p_{wt} + \alpha C_w^{rc} r_{wt}) \quad (5.1)$$

Subject to:

$$p_g^{min} \bar{U}_{gt} \leq p_{gt}, \forall g, t \quad (5.2)$$

$$p_{gt} + r_{gt} \leq P_g^{max} \bar{U}_{gt}, \forall g, t \quad (5.3)$$

$$0 \leq r_{gt} \leq R_g^{10} \bar{U}_{gt}, \forall g, t \quad (5.4)$$

$$\sum_{g \in G} r_{gt} + \alpha \sum_{w \in W} r_{wt} \geq p_{gt} + r_{gt} + \sum_w \xi_{wt}, \forall g, t \quad [\gamma_{gt}] \quad (5.5)$$

$$\xi_{wt} \geq p_{wt} - (p_{wt}^f - \beta \sigma_{wt}), \forall w, t \quad (5.6)$$

$$p_{gt} - p_{g,t-1} \leq R_g^{10}, \forall g, t, \bar{U}_{gt} = 1, \bar{U}_{g,t-1} = 1 \quad (5.7)$$

$$p_{g,t-1} - p_{gt} \leq R_g^{10}, \forall g, t, \bar{U}_{g,t-1} = 1, \bar{U}_{gt} = 1 \quad (5.8)$$

$$p_{wt} + r_{wt} \leq p_{wt}^f, \forall w, t \quad (5.9)$$

$$p_{kt} - B_k(\theta_{nt} - \theta_{mt}) = 0, \forall k, t \quad (5.10)$$

$$-P_k^{max} \leq p_{kt} \leq P_k^{max}, \forall k, t \quad (5.11)$$

$$\sum_{g \in g(n)} p_{gt} + \sum_{k \in \delta^+(n)} p_{kt} - \sum_{k \in \delta^-(n)} p_{kt} + \sum_{w \in w(n)} p_{wt} = d_{nt}, \forall n, t \quad [\delta_{nt}] \quad (5.12)$$

$$p_{wt}, r_{wt} \geq 0, \forall w, t. \quad (5.13)$$

In the above formulation, αr_{wt} is the scheduled reserve from wind. Equation (5.9) states that the scheduled energy plus an up-scaled version of the reserve should not exceed

the forecast. The descriptions of the other constraints are similar to what was described in chapter 3.

5.4. Contingency Analysis

To evaluate the efficiency of the proposed training-based policies in the market structure, a contingency analysis procedure has been performed. After the energy and reserve capacity are cleared in the SCED, the output schedule of the SCED structure is tested against a combination of different scenarios of wind and the single generator contingency events. The expected reserve activation payments for each resource are calculated based on the results of this contingency analysis stage.

The following formulation describes the redispatch following a combined contingency event.

$$\begin{aligned} \text{Min} \sum_t (\sum_g (C_g^{re} r_{gct}) + \sum_w (C_w^{re} r_{wct}) + \sum_w (C_p + C_w^{re}) p_{wct}^{penalty} \\ + \sum_n C_c^n (ls_{nct}^+ + ls_{nct}^-)) \end{aligned} \quad (5.14)$$

Subject to:

$$p_{kct} - B_k(\theta_{nct} - \theta_{mct}) = 0, \forall k, t \quad (5.15)$$

$$-P_k^{max} \leq p_{kct} \leq P_k^{max}, \forall k, t \quad (5.16)$$

$$\begin{aligned} \sum_{g \in g(n)} (p_{gt} + r_{gct}) + \sum_{k \in \delta^+(n)} p_{kct} - \sum_{k \in \delta^-(n)} p_{kct} + \sum_{w \in w(n)} (p_{wt} + r_{wct}) + \\ ls_{nct}^+ - ls_{nct}^- = d_{nt}, \forall n, t \quad [\lambda_{n,t}^c] \end{aligned} \quad (5.17)$$

$$r_{gct} \leq r_{gt}, \forall g, c, t \quad (5.18)$$

$$-r_{gct} \leq r_{gt}, \forall g, c, t \quad (5.19)$$

$$P_g^{min} \bar{U}_{gt} N_c^g \leq p_{gt} + r_{gct} \leq P_g^{max} \bar{U}_{gt} N_c^g, \forall g, c, t \quad (5.20)$$

$$-r_{wct} \leq \alpha r_{wt} + p_{wct}^{penalty}, \forall g, c, t \quad (5.21)$$

$$0 \leq p_{wt} + r_{wct}, \forall w, c, t \quad (5.22)$$

$$P_{wt} + r_{wct} + rr_{wct} \leq W_{wct}, \forall w, c, t \quad (5.23)$$

$$rr_{wst}, ls_{nct}^+, ls_{nct}^-, p_{wct}^{penalty} \geq 0, \forall w, c, t. \quad (5.24)$$

Parameter W_{wct} in Equation (5.23) represents the realized power output of the wind farm and parameter N_c^g in Equation (5.20) is 0 if generator g is experiencing a contingency and 1 otherwise.

5.5. Market Settlement

In most electricity markets energy and ancillary services are cleared together using an optimization model that includes both energy and reserve bids in the objective function [54]. The optimization procedure chooses the lowest submitted bids to satisfy all physical and operational constraints.

Prices are calculated based on dual variables from the market model and generators are compensated based on these dual variables. Specifically, locational marginal prices (LMPs) are used to settle energy compensations and reserve marginal prices (RMPs) are used to settle reserves compensations. The LMP for each node is the shadow price of the power balance equation (5.12) at that node. Load payments are calculated based on LMPs:

$$LP = \sum_{n,t} d_{nt} \delta_{nt} \quad (5.25)$$

The generators are entitled to payments for scheduled energy as well as the reserve capacity and reserve activation. Energy and reserve capacity payments are computed based

on LMPs and RMPs. In the presented formulation, the RMP is the nonzero shadow price (for the binding constraint) for (5.5).

The reserve activation payments are only made if the generator responds in a contingency event. The expected activation payment in such a payment scheme can be formulated as:

$$RAP_{g,t} = \sum_{c \in S} \pi_c \{ r_{gct} \lambda_{n(g),t}^c \} \quad (5.26)$$

where, π_c is the probability of contingency scenario c and $\lambda_{n(g),t}^c$ is the dual variable for (5.17). Here, $\lambda_{n(g),t}^c$ is a shadow price that reflects the marginal value of reserve for contingency c . The probability of each contingency is defined as the product of the probability of the related wind scenario and the probability of the respected generator contingency event. The probabilities of generator contingencies are calculated based on the FOR values of generators. The payments in (5.26) are the expected compensations for the reserve providers based on their corresponding activated services, which is exercised for individual contingencies.

5.6. Quality of Service

When a resource is scheduled to provide contingency reserve capacity, it is supposed to be able to dispatch that amount. If the pre-scheduled amount of reserve cannot be activated during a re-dispatch, then the resource provides a lower quality of service (QOS) than anticipated. Based on the scheduled capacity of reserve from renewables, (5.21) describes how the renewable resource is performing in exercising reserve. Here, variable r_{wct} measures how much reserve is dispatched from the resource w , where $p_{wct}^{penalty}$ represents the shortfall below the scheduled downward reserve.

The objective function (5.14) motivates a small shortfall. The large penalty included in the objective function prevents renewable resource from going below the scheduled downward reserve.

In this section, the notion of quality of reserve (QOS) is defined to reflect the efficiency of the training algorithm in deriving reserve policies for renewables. QOS can also be viewed as an indicator for measuring the efficiency of a model. The quality of service for reserve (QOS_r) can be characterized by the proportion of reserve capacity which is deliverable for each contingency in real time. An efficient model is expected to have a quality of reserve closer to one, indicating that a large portion of reserve capacity procured based on reserve policy is deliverable in real time.

Quality of service for energy (QOS_E) provided by wind resource for each contingency scenario is measured by the behavior of the wind resource in the re-dispatch corresponding to that scenario. Note that, in this chapter, the redispatch is performed to minimize the total cost as described in (5.14).

In the presented market model, a single variable has been used for both upward and downward reserve. Therefore, different possible situations have been categorized into multiple groups, as described below, to quantify the quality of service for each probable situation [91].

If the implemented reserve (r_{wct}) is positive, this indicates that the wind generator has satisfied the promised energy, and therefore, $QOS_E = 1$. As for reserve, if the available wind power is more than the total scheduled energy and reserve, $QOS_r = 1$. Otherwise,

$$QOS_r = \max\left(1, \frac{r_{wct}}{\alpha r_{wt}}\right). \quad (5.27)$$

If the implemented reserve (r_{wct}) is negative, two situations are possible:

1) The actual realized wind power is greater than the total energy and reserve implemented from wind: in this case, the quality of energy service and the quality of reserve service are both equal to 1.

2) The realized wind is equal to the total energy and reserve implemented: in this case, the quality of service for energy product is calculated based on the proportion of the scheduled energy that has been provided. This proportion can be described as:

$$QOS_E = 1 + \frac{r_{wct}}{p_{wt}}. \quad (5.28)$$

The quality of service for reserve product in this situation is calculated based on the proportion of the scheduled reserve that has been provided:

$$QOS_r = \max(0, 1 - \frac{\text{penalty } p_{wct}}{\alpha r_{wt}}). \quad (5.29)$$

The above notions are used to measure the efficiency of the proposed policy method. The following section provides the numerical results.

5.7. Numerical Results and Analysis

The analysis in this section evaluates the prediction based policy and its counterpart where no policy is applied. The prediction-based policies are selected based on the procedure described in chapter 3.

The policy (generated offline) is implemented in a deterministic real-time framework, i.e., a deterministic dispatch procedure described in section 5.3. The hour-ahead SCED is solved based on the policy derived for the closest trained operating solution.

5.7.1. Data and Simulation Setup

The proposed structure has been applied to the IEEE RTS-96 test system [84]. The test system is modified by integrating a 1500 MW wind farm, at bus 40, which accounts for roughly 30% of the total system-wide generation capacity. The wind generation data of a wind farm for the year 2010 [26] is used after proper scaling to suit the chosen wind farm capacity.

The hour-ahead model includes 10-minute intervals across a 1-hour horizon. For the current simulation, the Markov forecast for the 9 AM-12 AM epoch is used [26]. The load classification used in this study is based on data from RTS-96 test system [84]. All simulation results presented are for month April, henceforth. The probabilities of generator contingencies are calculated based on the FOR values provided in the IEEE RTS-96 data [84]. In reality, FOR of each generator unit type is calculated based on historical operation performance [57].

5.7.2. Prediction-based Policy Method and Base Case Method Comparison

The solution of this look ahead SCED is analyzed across probable instances including various possible wind outcomes and possible contingencies. Each solution is tested against the combination of 100 wind scenarios generated based on the initial wind level and all the $N-1$ generation contingencies. The model contains 99 generators and, therefore, 99 generation contingency instances. Adding the wind scenarios, a total of 9900 instances are modeled for each solution.

In order to analyze the performance of this method, a set of base-case studies with no policies have been run where the operator counts on the wind predicted mean ($\bar{\alpha} = 1$).

Table 5.1 through Table 5.4 present the average market results over all the modeled instances. Table 5.1 summarizes production cost, load payments and energy revenues, and Table 5.2 presents the quality of service for each tested wind level. The results show that the prediction-based policy achieves a higher average quality of service. Table 5.3 and Table 5.4 presents the revenues from reserve markets for conventional and renewable producers. The capacity payments and the activation payments are reported in Table 5.3 and Table 5.4 respectively. The proposed policy results in a higher payment for reserves to renewable resources. Table 5.5 compares the utilization of wind in the two methods. Overall, the policy method schedules more reserve from wind and incurs less penalty for not being able to provide the scheduled power. The average wind curtailment shows a slight increase in the policy method. Fig. 5.1 and Fig. 5.2 represent the quality of energy and quality of service across contingency scenarios. These results demonstrate that prediction based policy can significantly improve the reliability of the service provided by wind generators.

Table 5.1. Market measures: average system results

Win d level (%)	Production cost (\$/h)		Load payment (\$/h)		Energy revenue (\$/h)	
	Base case	Prediction- based	Base case	Prediction- based	Base case	Predic- tion-based
3	264011.2	263781.7	533273.5	523411.2	493606.9	495792.4
6	254993.7	254781.2	533273.5	513548.9	483308.9	487881.7
9	245418.7	245212.3	521838.5	517317.1	470107.7	474790.4
12	235545.7	235545.7	515750.4	515750.4	450450.5	450450.5
15	222118.7	221919.3	621048.2	514863.4	417451.2	433600.8
18	213208.5	213136.8	609915.7	514863.4	380112.5	430750.6
21	206035.4	205900.1	525703.1	525888.1	296385.9	300700.4
24	197182.3	196821.9	526082.2	528234.8	281678.7	274561.6
27	190022.2	189828.1	526799.7	528234.8	266709.2	268368.4

Table 5.2. Quality of service: average system results

Wind level (%)	Reserve QOS		Energy QOS	
	Base case	Prediction-based	Base case	Prediction-based
3	0.7693	0.9879	0.800	0.8815
6	0.5435	0.9497	0.810	0.9111
9	0.1404	0.9557	0.738	0.9068
12	0.0359	0.0359	0.619	0.6197
15	0.3991	0.6604	0.854	0.8759
18	0.3907	0.9443	0.809	0.9291
21	0.3507	0.8685	0.878	0.9491
24	0.3567	0.9449	0.752	0.9124
27	0.3572	1	0.872	0.9915

Table 5.3. Reserve capacity payments: average system results

Wind level (%)	Reserve capacity revenue (conventional generators) (\$/h)		Reserve capacity revenue (wind generator) (\$/h)	
	Base case	Prediction-based	Base case	Prediction-based
3	16434.76	6960.85	1062.90	716.49
6	16434.76	5692.86	984.262	971.3499
9	16306.72	3600.86	1388.25	1602.689
12	15974.01	15974.0	1582.65	1582.653
15	13022.48	5557.59	1979.55	1174.964
18	12364.79	2379.1	1637.68	2239.988
21	7669.869	3978.60	0	1345.384
24	6746.796	174.49	0	1030.558
27	6356.556	0	0	215.5465

Table 5.4. Reserve activation payments: average system results

Wind level (%)	Reserve activation revenue (conventional generators) (\$/h)		Reserve activation revenue (wind generator) (\$/h)	
	Base case	Prediction-based	Base case	Prediction-based
3	15585.05	14125.87	66.69	166.25
6	5444.044	5232.83	7.362	266.50
9	5087.439	3657.905	1.2246	202.54
12	5859.289	5859.289	0	0
15	3528.479	3252.916	1566.281	1431.56
18	8352.536	5262.85	0.0696	214.99
21	5458.106	5162.909	0.8255	350.77
24	13210.2	4258.596	0.1707	399.33
27	6024.633	0	0.1512	2818.54

Table 5.5. Wind utilization measures: average system results

Wind level (%)	Scheduled reserve from wind (MW)		Curtailed wind power (MW)		Wind penalty (\$/h)	
	Base case	Prediction-based	Base case	Prediction-based	Base case	Prediction-based
3	25.22	36.81	3.322	4.300	133.4814	37.5581
6	23.35	53.84	0.355	0.791	155.6067	42.2518
9	33.18	97.65	0.084	0.544	255.4437	25.6938
12	38.63	38.64	0	0	415.446	415.446
15	50.94	68.99	0.024	0.109	84.7621	59.0765
18	49.92	144.21	0.017	0.503	380.9586	25.5383
21	0	92.57	0.102	1.051	512.1057	62.8103
24	0	194.42	0.011	0.615	934.6266	40.1877
27	0	179.62	0.047	4.577	767.2197	0.6998

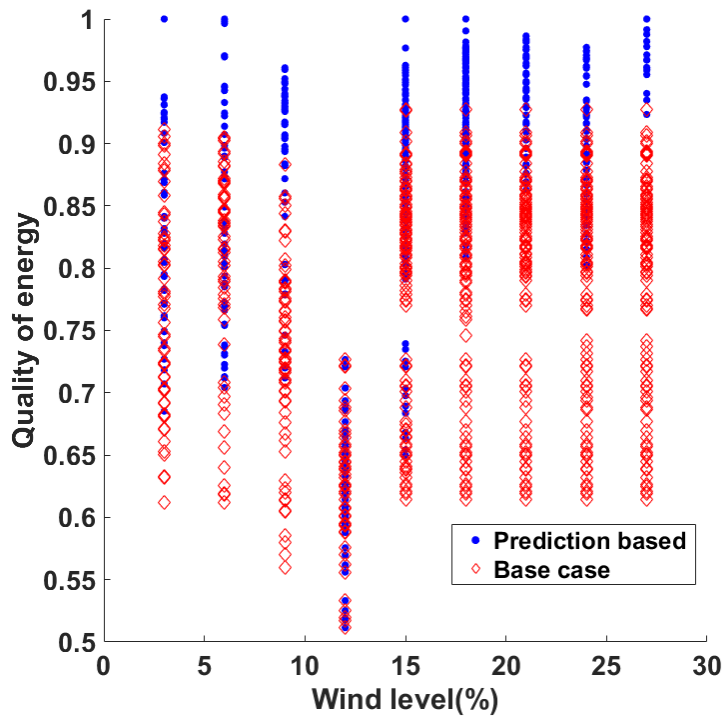


Fig. 5.1. Quality of energy service from wind farm for different wind scenarios.

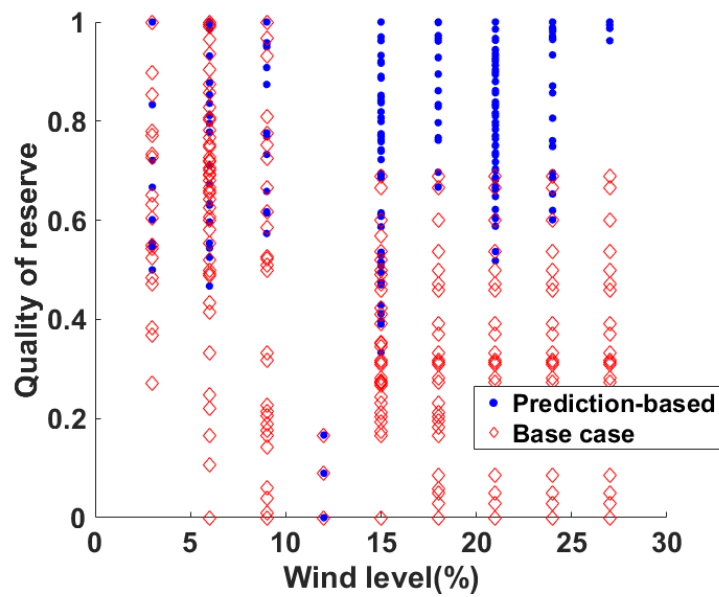


Fig. 5.2. Quality of reserve service from wind farm for different wind scenarios.

5.8. Conclusions

Integration of renewable generation increases the uncertainty and variability that the operator must handle. Utilizing the concept of wind flexible reserve margin allows the operator to allocate a discounted amount of wind for energy, leaving a reserve margin to hedge against uncertainty. This study analyzes the utilization of such reserve margins in the ancillary service procurement.

This chapter compares the impacts of two different scheduling models, a base case model and a prediction based model. The prediction-based model has a deterministic structure and uses a flexible reserve margin based algorithm, which has been applied to train offline policies for discounting wind generation and scheduling energy and reserve in the presence of wind. The base case uses a deterministic SCED, which does not discount wind generation.

The market implications of transitioning to the prediction-based approach are demonstrated. The results suggest that the prediction-based model obtains higher quality of service from renewables. The results show that the average quality of energy service is roughly improved by 10% and the average quality of reserves is roughly improved by 30%. The prediction-based approach was also found to have lower load payments.

Future work can extend the proposed method to account for other types of uncertainty and locational aspects of the reserves. The approach discussed in this chapter can improve the reliability of reserve products provided by renewables.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1. Conclusions

This dissertation discussed the ways employing emerging computational advances in system operation policies can improve the flexibility of the electricity industry in presence of high penetration of wind generation.

In chapter 2, a background review was presented on the topics included in this dissertation. First, a review of wind power forecasting approaches was presented. Subsequently, the detailed steps of the Markov chain model-based wind generation forecast, which is the method used for generating wind scenarios in chapter 3, chapter 4, and chapter 5, was described.

In chapter 3, a combined hour-ahead dispatch and reserve scheduling framework was proposed by determining a flexible wind reserve margin. Utilizing the concept of flexible wind reserve margin allows the operator to allocate a discounted amount of wind for energy, leaving a reliability margin to hedge against uncertainty. The extra production of the wind farm can then be used for balancing purposes. A finite-state Markov chain 10-minute-ahead wind power forecast model, based on spatio-temporal analysis, was utilized to calculate the conditional probability distribution of the wind farm generation. The presented framework was used to find the appropriate level for allocating wind based on the predicted output. Numerical studies, demonstrated the significant benefits obtained by incorporating the flexible wind reserve margin using a Markov-chain-based forecast. The results communicate that scheduling the flexible wind reserve margin will allow the operator to increase the reliability margin of the system while reducing the total cost. Discounting the

scheduled generation from wind would improve the reliability by handling the uncertainty at an early stage. It also addresses the existing cost trade-off between scheduling generation from wind and the risk associated with wind farm uncertainty and improves the overall cost of supplying the demand.

In chapter 4, the possibility of exploiting offline stochastic calculations for training deterministic operation policies is investigated. An offline policy generation technique is proposed based on stochastic reserve margin scheduling to hedge against the real-time uncertainty of wind farm generation. A flexible reserve margin based algorithm has been applied to train offline policies for discounting wind generation and scheduling energy and reserves in presence of wind. A scenario-based stochastic programming approach is leveraged to capture the effect of various possible wind scenarios based on short-term wind forecast and the loading conditions of the system. A testing method is derived to assess the performance of the policies obtained through the proposed training procedure for scheduling wind reserve margin. The proposed approach is tested and the costs are compared to those obtained by using ad-hoc rules to analyze the effectiveness of the presented model in handling uncertainty. The results show that the training based on the risk-aware scheduling can reduce the overall cost, while not imposing the burden of stochastic programming in real-time operation.

In chapter 5, the impacts of utilizing reserve margin policies to schedule energy and reserve from renewables were studied. The market implications of implementing this model in ancillary service procurement were analyzed. Subsequently, the impact of two different scheduling models were compared; a base case model and a prediction based model. The prediction-based model uses a flexible reserve margin based algorithm, which

has been applied to train offline policies for discounting wind farm generation and scheduling energy and reserve in the presence of wind. The market implications of transitioning to the prediction-based approach are demonstrated. The results suggest that the prediction-based model obtains higher quality of service from renewables while having lower production cost and load payments.

6.2. Future Work

In this section, additional future research directions are proposed to supplement the current work. In this dissertation, the focus has been on the benefits of wind reserve margin from the viewpoint of the system operator who tries to minimize the operating cost. One direction for future work is to analyze the impact of deploying wind reserve margin policies in a comprehensive market structure. In such a model, the point of view is that of the wind power producer. Wind power producers that take part in the electricity energy and reserve markets can be considered via a market mechanism in which the wind producers can update their decision, taking into account the incurred risk and utilizing the updated forecast information. In other words, a risk-based study can be performed by the wind power producer to balance its expected profits from participation after providing reserve margins. This mechanism should take into account the probability of reserve shortfall and be designed in a way that power producers, including wind power producers, procure reserves in real time if they cannot provide the promised reserve.

The results of the present study suggest that the quality of service from renewables is increased by implementing the reserve margin policies. The increase in quality of service can be described in terms of the failure rate for wind power producers. Another future research direction, therefore, would be to analyze the impact of such policies on assigning

capacity credits to wind farms. Other aspects like the environmental impacts of these policies, such as carbon emission, can also be studied through observing the change in generation and ramping of conventional generators.

Future work can also extend the proposed method to account for other types of uncertainty such as transmission contingencies and locational aspects of the reserves. Other data mining approaches such as multi-target regression trees can be used to come up with policies for system operation considering the impact of transmission congestion patterns. A further step can thus, be to ensure deliverability of the reserves scheduled using the proposed policies. For example, the line flow patterns in a transmission network can be used as an additional input to the learning process that decides reserve margin policies.

In this research, wind farms have been considered as individual entities contributing to the reserve procurement through reserve margins. A more advanced case would allow a collection of neighbor wind farms to produce a cumulated amount of reserve. A future research direction would be to determine the reserve providing capability of a wind farm cluster based on the power generation forecast for a large area in the system, the correlations of the wind farms in the cluster, and the deliverability of the scheduled reserve based on network congestion patterns and transmission contingencies.

The analysis performed in this thesis are based on stochastic scenario-based optimization. Other approaches such as robust optimization can also be leveraged to perform stochastic analysis to generate operational policies. Robust optimization, for example, can be used to mitigate the uncertainty for a given continuous uncertainty set. More accurate forecast can then be utilized in a scenario-based structure in a near-real-time procedure when

most of the uncertainty has been revealed. The analysis of other mathematical frameworks and their performance remains as a future possible research direction.

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