Scheduling strategy design for unit commitment with energy storage system and solar energy resource

Qin, Lingzi

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SCHEDULING STRATEGY DESIGN FOR UNIT COMMITMENT WITH ENERGY STORAGE SYSTEM AND SOLAR ENERGY RESOURCE

QIN LINGZI

SCHOOL OF ELECTRICAL & ELECTRONIC ENGINEERING

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School of Electrical & Electronic Engineering

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Abstract

Unit commitment means the pre-setting scheduling and arrangement of the electrical generator operation. It plays a critical role in the power system optimization problem which aims to utilize power resources rationally and enhance the efficiency of operational economy under the condition of safe operation of power system. With the high penetration of renewable energy, which increases deregulation when renewable energy is fed into the traditional power system and attention of safety operation in power system, there is a growing focus on optimization with uncertainties. This thesis proposes a unit commitment model to minimize the impact of uncertainty. The scheduling strategy is composed of two main cases which correspond to the two intervals of the probability distribution of the solar power output. The energy storage system is coordinated to guarantee the power system security when the margin of error is beyond the confidence interval of solar power probability. In order to deal with both volatile load demand and the solar power, we apply a normal probability distribution to define net load demand. The scheduling strategy is divided into two intervals based on its confidence interval, and interval optimization is adopted to reduce the complexity of this optimization problem in the confidence interval. Energy storage system is flexible to maintain the power balance with an acceptable cost and maximize the utilization of the renewable energy in the non-confidence interval. The numeri-

cal results of 14-bus and 30-bus power systems demonstrate the effectiveness of the proposed scheduling strategy which could provide economical, adaptive and calculation time-saving features.

Acknowledgement

My deepest gratitude goes first and foremost to my supervisor Professor Hu Guoqiang for giving me this precious opportunity to work my Master of Engineering programme under his constant encouragement and guidance. I have learnt from our meeting and other interactions with him and experienced how optimistic and friendly he was. Without his consistent instruction, much progress in research and completion of my degree programme would not have been made.

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Last but not least, my thanks would go to my parents for their loving considerations and constant support during my study.

Abbreviations

UC	Unit Commitment.
PL	Priority List.
DP	Dynamic Programming.
LR	Lagrangian Relaxation.
MIP	Mixed Integer Programming.
TS	Tabu Searching.
GA	Genetic Algorithm.
SA	Simulated Annealing.
PSO	Particle Swarm Optimization.
ACO	Ant Colony Optimization.
BD	Benders Decomposition.
$PTDF$	Power Transfer Distribution Factors.
RES	Renewable Energy Resources.
ESS	Energy Storage System.

Nomenclature

Indexes

i Index of traditional generators.

s Index of photovoltaic energy units.

e Index of storage units.

b Index of buses.

d Index of loads.

l Index of transmission lines.

t Index of time periods, generally based on an hour.

Sets

N_g Set of traditional generators.

N_s Set of photovoltaic energy units.

N_e Set of storage units.

N_t Set of scheduling periods.

N_d Set of loads.

N_b Set of buses.

N_l Set of transmission lines.

$C_{g,t}$ Operation cost of traditional generator i at time t.

$C_{s,t}$ Operation cost of photovoltaic energy unit s at time t.

$C_{e,t}$ Operation cost of energy storage unit e at time t.

T_i^{on} Minimum time period traditional generator i must be initially online.

T_i^{off} Minimum time period traditional generator i must be initially offline.

T_{i0}^{on} Minimum time period traditional generator i has been online prior to the first hour.

T_{i0}^{off} Minimum time period traditional generator i has been offline prior to the first hour.

T_i^u Minimum time period traditional generator i must remain online once the unit is started up.

T_i^d Minimum time period traditional generator i must remain offline once the unit is shut down.

Parameters

PG_i^{max} Maximum real power output of traditional generator i.

PG_i^{min} Minimum real power output of traditional generator i.

$P_{d,t}$ Load demand at load bus d at time t.

$P_{s,t}^f$ Forecasted output of photovoltaic energy unit s at time t.

$P_{s,t}$ Output of photovoltaic energy unit s at time t.

RU_i Ramp up hourly limits of traditional generator i.

RD_i Ramp down hourly limits of traditional generator i.

SU_i Startup ramp limits of traditional generator i in an hour.

SD_i Shutdown ramp limits of traditional generator i in an hour.

$T_{l,b}$ Element of the power transfer distribution factor matrix associated with line l and bus b.

F_l Power flow limits of transmission line l.

$E_{e,t}$ Energy stored in storage unit e at time t.

E_e^{min} Minimum energy stored in storage unit e.

E_e^{max} Maximum energy stored in storage unit e.

η_e^C Charging efficiency of storage unit e.

η_e^D Discharging efficiency of storage unit e.

$P_e^{C,min}$ Minimum charging power of storage unit e.

$P_e^{C,max}$ Maximum charging power of storage unit e.

$P_e^{D,min}$ Minimum discharging power of storage unit e.

$P_e^{D,max}$ Maximum discharging power of storage unit e.

Variables

$I_{i,t}$ On/off status of traditional generator i at time t.

I_{i0} Initial commitment status of traditional generator i.

$p_{i,t}$ Real power output of traditional generator i at time t.

$p_{b,t}$ Real import/export power from/to bus b at time t.

$P_{e,t}^C$ Charging power of storage unit e at time t.

$P_{e,t}^D$ Discharging power of storage unit e at time t.

$u_{e,t}^C$ Charge mode of storage unit e at time t.

$u_{e,t}^D$ Discharge mode of storage unit e at time t.

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Chapter 1

Introduction

1.1 Background

There is a great variation in the load demand of power system: load demand varies with the periodic fluctuation changes in a mix of issues, such as human civilization and production of life activities, or caused by other factors like the weather. For instance, people use more electricity on weekdays than Saturdays, more on Saturdays than on Sundays, and at an extreme higher rate on peak hours than off-peak hours [5–8]. In order to meet the load demand in peak hours, generating units will be online during the peak period which causes generating units generate the minimum energy during the off-peak period without power system operation strategy. Therefore, the problem confronting the power system operation is how to decide status of each generating unit, including on/off-line state and output.

The basic goal of power system operation is to meet the load requirement which is not a constant but varies. The preferable strategy in power system to decide generating units status takes economical aspects into account. In other words, it is vital in power system operation to satisfy the load demand by using different combinations of generating units with operation cost minimization. Unit Commitment (UC) is the one of the best solutions which is proposed to provide high-quality electricity in a safe and economical manner.

The objective of Unit Commitment (UC) [9] is, in a certain scheduling period, to make rational arrangement of the electrical generator operation for the sake of economical and safe operation, under conditions where these arrangements satisfy different operation constraints.

Therefore, the output of UC is a mix of generating units which includes commitment status and power output, moreover, the general objective of UC is to minimize the total operation cost, such as fuel cost [10] and start-up cost [11], as well as some specific costs under a certain circumstance [12]. In addition, in order to ensure the safety of power system operation, it needs to satisfy all of the constraints [10] such as generating unit physical constraints (e.g., capacity and ramping down/up limits).

UC, with the characteristic of being high-dimensional, nonconvex and distributed, is a highly nonlinear optimization problem, which is mathematically a NP-Hard problem [13] as UC uses binary variables to show the generating units status (ON/OFF) with many constraints. The UC problem will become very difficult and complicated when the scale of the problem increases. For many years, many researchers have developed a variety of solution methodologies from early approaches in the basis of Priority List (PL) [14–16], Dynamic Programming (DP) [5, 7, 17–19] and Lagrangian Relaxation (LR) [20–22] to the advanced approaches in the basis of Mixed Integer Programming (MIP) [23–25] which is the most commonly adopted. Furthermore, artificial intelligence is being used to solve the UC problem, i.e., Tabu Search (TS) [26, 27], Genetic Algorithm (GA) [28–30], Simulated Annealing (SA) [31–33], Particle Swarm Optimization (PSO) [34–36], and Ant Colony Optimization (ACO) [37,38]. This thesis focuses on MIP that is the most rife methods.

Since UC problem aims to make more effective and economical decisions in power system operation, the planning horizon is very important to affect its accuracy and complexity. The exact long-term UC problem [39–41] is not practical enough, as the extrapolation of UC model is inadequate, e.g., prices change and technologies advance, etc. On the other hand, it is a great degree of difficulty to solve such a complicated problem with a mass of constraints which means that the computation time is exorbitant. Considering uncertainty of renewables, this thesis addresses short-term UC problem (day-ahead and hourly-ahead) rather than long-term UC problem (seasonal and yearly).

1.2 UC Problem Formulation

The UC problem formulation mimics the standard power system so that it is an adequate model of equipment and grid. Genearlly, the more complicated and practical model is, the more difficulty and time-consuming the calculation is. The considered short-term UC problem can be formulated as follows.

Objective:

$$min \sum_{N_t} \sum_{N_g} C_{g,t} \tag{1.1}$$

The objective of generic UC problem (1.1) is to minimize generating units operating cost $C_{g,t}$, which contains fuel cost $F_i(p_{i,t})$ and startup cost $ST_i(u_i)$ that is considered as a constant.

$$C_{g,t} = F_i(p_{i,t}) + ST_i(u_i) \tag{1.2}$$

The fuel cost $F_i(p_{i,t})$ is widely modeled with a curve [42] given below.

$$F_i(p_{i,t}) = a_i p_{i,t}^2 + b_i p_{i,t} + c_i \tag{1.3}$$

where $a_i > 0$, $b_i > 0$ and $c_i > 0$ are the coefficients.

Subject to constraints:

Power balance

$$\sum_{N_d} P_{d,t} = \sum_{N_g} p_{i,t} \tag{1.4}$$

Physical output limits on generating units

$$PG_i^{min} I_{i,t} \leq p_{i,t} \leq PG_i^{max} I_{i,t} \tag{1.5}$$

Ramping rate

$$p_{i,t} - p_{i,t-1} \leq RU_i I_{i,t-1} + SU_i(I_{i,t} - I_{i,t-1}) + PG_i^{max}(1 - I_{i,t}) \tag{1.6}$$

$$p_{i,t-1} - p_{i,t} \leq RD_i I_{i,t} + SD_i(I_{i,t-1} - I_{i,t}) + PG_i^{max}(1 - I_{i,t-1}) \tag{1.7}$$

Grid limits

$$-F_l \leq \sum_{N_b} T_{l,b}(\sum_{N_g(b)} p_{i,t} - \sum_{N_d(b)} P_{d,t}) \leq F_l \tag{1.8}$$

Minimum certain period

Generating units must be initially online/offline for a certain time period, they have been online/offline prior to the first hour and remain online/offline for a certain number of hours once started up/ shut down.

1.3 Renewable Energy Resources

Nowadays, it is widely considered that human activities have meaningfully changed global environment and catastrophic climate change is one of the most serious consequences. The concentration of carbon dioxide (CO_2) has significantly risen from 290 ppm (part per million) over the last 800,000 years to above 380 ppm [43] and CO_2-free power production is thus going to become an increasing concern worldwide.

Development and the use of renewable energy resources (RES) has become the important measure to achieve the above goal – CO_2-free power production. RES consists of solar energy, geothermal energy, wind energy, waves energy, tides energy, osmosis energy, hydroelectric power, biogenic energy. Photovoltaics and wind energy are two main areas because they are non-pollution, economic and abundant.

Solar energy is used for converting sun's energy into electrical power. There are two major conversations: direct and indirect. The direct conversation, as the name implies, changes the energy of the sun into electricity directly in solar photovoltaic (PV) panels without moving part, which is thus named as termed solar photovoltaic energy [44]. The indirect conversation, which is considered as solar thermal energy, most commonly takes place in water or other liquids to generate heat. Besides, solar photovoltaic energy is more widely used than solar thermal energy since the former one utilizes directly energy that sun reaches the earth, which is around 8000 times than the world sum usage of nuclear energy and fossil fuels [45]. The photoelectric cell, where solar energy is converted into electricity, is highly efficient – over 20% efficiency, that is, 20% of solar energy used is able to be converted into electrical power.

Wind energy is second to solar energy as the most prevalent renewable energy type. The base concept of wind energy is rotational energy of turbines by wind speed into electrical current, and then the specific converter input electrical current to the power grid [44]. The facilities are always located on high elevations where winds are stronger and use tall turbines to catch more winds.

1.4 Unit Commitment with RES

With a better understanding of RES, great attention has been paid to the RES studies over the world because of the wide use of RES. Compared with the traditional power generation, RES, such as wind and photovoltaic generation, can contribute to the improvement of the whole energy structure, enhance energy supply and improve environment in the framework of sustainable development. Meanwhile the technical challenges of integrating RES into the distributed power system while running and safe-guarding an efficient and economic power network have more concerns.

Although the UC problem has advanced and evolved over the years in the existing literature, recent challenges are from the increasing penetration of RES, which have attracted a vast amount of attention all over the world about improvements of UC models and algorithms. With the characteristic variability and uncertainty, high-level RES integrated power system causes higher flexibility requirements of power system to cope with fast and great fluctuation in RES.

The novel unit commitment model is used to solve the problem about the distribution of traditional generators with the objective of minimizing the operation cost [11,42,46,47] without the consideration of uncertainties in RES. This means the deterministic UC model has not kept up with requirements of today's smart network with RES integration. The earlier method relies on conservative reserve requirements which is so-called reserve adjustment method, and it is widely utilized in power industry because of its practicality. [48–51] focus on the reserve requirements and analyze their levels in the basis of conventional criteria, e.g., system import change and the capacity of the largest generator. However, setting the extra generating units as reserves means extra costs, and thus, this scheme doesn't satisfy the economical aim of the UC problem, especially when the reserve requirements are decided to be larger by ad-hoc rules. Moreover, reserves are determined by systematic analysis which cannot handle insufficient problems of power system in real condition, such as load deviations.

To solve this problem, many researchers have directed their attention to UC models with intermittent nature source, including wind and photovoltaic resources. Stochastic unit commitment (SUC) [52] based on simulation scenarios solves this problem and improves operational economic efficiency in power systems. Numerous scenarios can be generated to realize possibilities of uncertain resources by direct discretization of relevant parameters or the sampling method based on a given probability distribution model. A sufficient condition for inactive constraints are established by using the MILP method to simplify SUC problem in [53]. Approaches to generate scenarios are MC sampling, one based on stability analysis and moment matching principles. In [54], the normal distribution model of load demand is discretized and mid-points are used to represent uncertain load demand. Sample scenario trees are studied to evaluate load forecast errors and generator outages to solve UC problem in [55–57]. The authors in [58, 59] investigate a SUC problem with high penetration wind power generation and uses scenarios method to simulate wind forecast uncertainties by sampling in certain probability distributions.In [60], a general survey on scenario tree algorithms is conducted. As the quantity and quality of scenarios play important roles in optimization via SUC solutions, the computational burden grows as more scenarios are considered.

Another method for solving this problem is robust unit commitment (RUC) which refers to the interval optimization [61]. Robust optimization has attracted great attention at present of research area where parameter uncertainty severely affects modeling framework for optimization [62–68]. Interval optimization requires the range of uncertainty rather than a probability distribution model for uncertainty. In addition to the loose requirement of uncertain data, the model is flexible which can be adjusted properly by different available information about model and the requirement to commitment accuracy [69, 70]. Load uncertainty is modeled by interval optimization in [71], which divides the problem into two subproblems and uses upper and lower bounds to obtain the solution. [72] proposes a two-stage adaptive model for solving the problem about nodal net injection uncertainty. The outer approximation technique is considered to develop a more practical solution methodology which is based on Benders Decomposition

(BD). [73] developes the robust optimization in the basis of BD to the security-constrained problem. Load and wind uncertainty construct uncertain intervals and eliminate the worst case which is no possibility to happen. Since RUC is sensitive to the setting of interval, large interval period which is set to guarantee the system security will deteriorate its economy operation.

In the following chapters, this thesis proposes a unit commitment model aiming at assessing the impact of the quality of forecasted value of uncertain resource and load demand. The forecasting method for PV generation depends on the solar irradiance level [74], and the volatile load demand can be modeled by load components [75]. In *Chapter 2*, this thesis focuses on the uncertain solar resource, meanwhile, the load demand is assumed to be a constant. Our proposed model divides the solar power output into two intervals, corresponding to the confidence interval of solar generation probability distribution, which can solve the over-conservative problems effectively, based on the concept of the RUC model. Different strategies are designed in different intervals of solar power output to improve the system security and optimize the model computing in a reasonable way. Energy storage system (ESS) [3, 76] is utilized in extreme case to realize peak clipping, valley filling to maximize the utilization of energy and guarantee the reliability of power system by following the change of power demand in power system. When both uncertain solar resource and load demand are considered, net load demand is defined due to the property of normal probability distribution in *Chapter 3*. Hierarchical scheduling strategy is designed to cope with different probability levels. In the high probability interval, interval optimization [71, 77] is adopted to reduce the computational difficulty. Energy storage system is regulated to compensate for the larger forecasting error which occurs in the low probability interval. In *Chapter 4*, the conclusions of this thesis are drawn and future research directions are discussed.

Chapter 2

Day-ahead Unit Commitment with Solar Resource

This chapter introduces the proposed UC model. The model assumptions are made in *Section 2.1*, and strategies with mathematical formulation are described in *Section 2.2*. In *Section 2.3*, this thesis summarizes the designed schedule as a framework. The proposed scheduling is implemented on IEEE 14-bus solar resource integrated test system in *Section 2.4*. Finally, we summarize the work mentioned previously and draw conclusions on results obtained in *Section 2.5*.

2.1 Model Assumption

The main assumptions of the proposed unit commitment model are listed as follows.

1) The ESS is deployed as an energy resource that is fully controlled by the system and operates in a way which maximizes the overall economic benefits for the whole power system.

2) Solar forecast output is based on historic solar radiation data. In order to

collect forecast solar radiation data and generate scenario sets, the mathematical model takes into account the difference between the solar radiation in different intervals and initial sampling scheme from a multivariate distribution. In this chapter, we focus on the forecasted error of solar power output and assume that the probabilistic model of the PV power output approximates a normal distribution model $N(\mu, \sigma)$ for simplicity as shown in Figure 2.2.1.

3) The proposed hourly UC is based on hourly day-ahead forecast of the load demand and the PV power output.

2.2 Adaptive Scheduling Strategy

The proposed day-ahead unit commitment strategy considers the forecasted solar power output to determine the states of traditional generators. For real-time dispatch, the proposed strategy is divided into two stages: base case (interval R1) and extreme case (interval R2 and R3), based on the deviation between forecasted solar power output and actual solar power output in each time period, as shown in Figure 2.2.2. This thesis considers $(1-\alpha)$ as the confidence level, and the confidence interval is $[P^l, P^h]$ as shown in Figure 2.2.1. Therefore, the base case in confidence level $(1-\alpha)$ has a greater probability while the extreme case in the level α is of lower chance, such as 95% versus 5%. In base case (interval R1) where the probability that solar power output falls in interval $[P^l, P^h]$ is quite high and the deviation is small, the power output of traditional generators can be adjusted to satisfy the operation of the whole power system. In extreme case, it can be divided into two sub-intervals R2 and R3. When there is no cloud, the solar radiation intensity is greater than the forecasted value in R2, which means that the solar output is higher than P^h. The requirement of system security will operate the energy storage system to charge the surplus power. When the sky is cloudy, the solar power output is smaller than the forecasted value in R3. The energy storage system is utilized to guarantee the power balance of the whole system by discharging power to compensate for the lack of power.

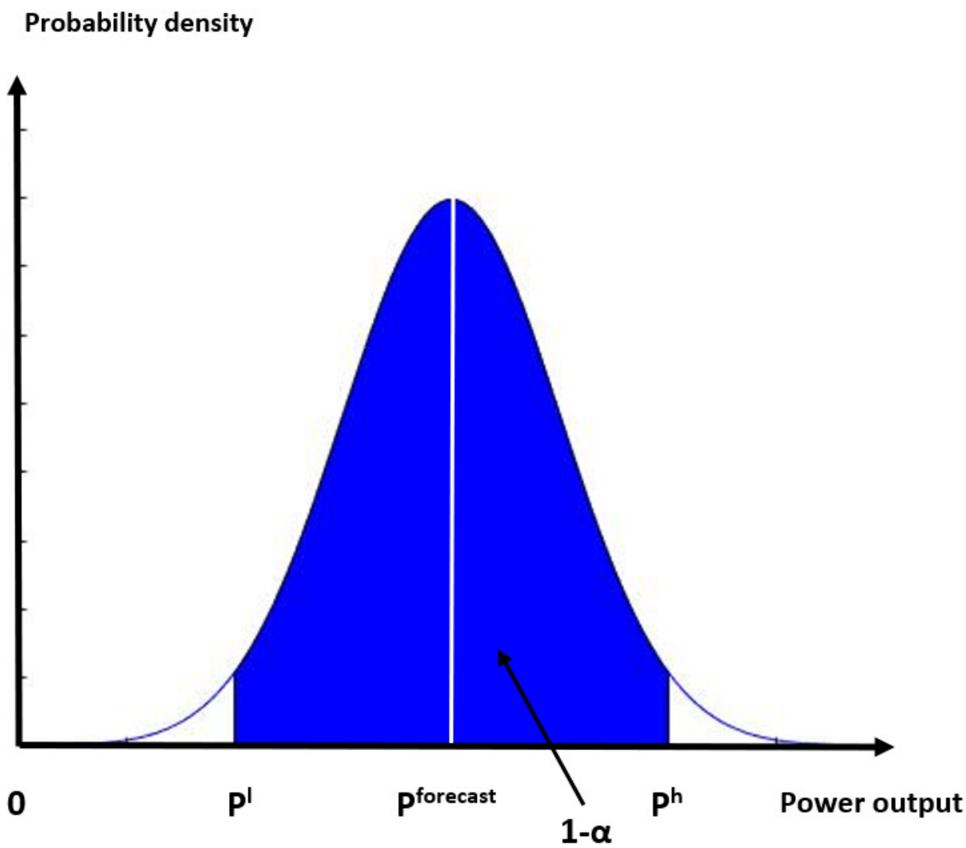

Figure 2.2.1: Probability distribution of solar power output

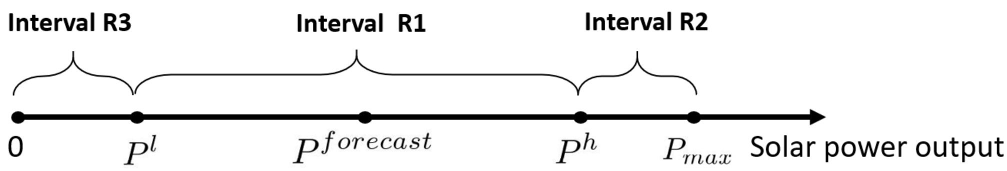

Figure 2.2.2: Interval division of solar power output

2.2.1 Day-ahead Unit Commitment

Objective Function

The objective function of the day-ahead UC model is formulated as

$$min \sum_{N_t} (\sum_{N_g} C_{g,t} + \sum_{N_s} C_{s,t}) \tag{2.1}$$

The objective function (2.1) consists of traditional generator operating cost $C_{g,t}$, and solar energy cost $C_{s,t}$.

The traditional generator cost $C_{g,t}$ contains fuel costs $F_i(p_{i,t})$ and startup costs $ST_i(u_i)$.

$$C_{g,t} = F_i(p_{i,t}) + ST_i(u_i) \tag{2.2}$$

The fuel costs $F_i(p_{i,t})$ are widely considered as a quadratic function [42] given as follows.

$$F_i(p_{i,t}) = a_i p_{i,t}^2 + b_i p_{i,t} + c_i \tag{2.3}$$

where $a_i > 0$, $b_i > 0$ and $c_i > 0$ are the coefficients.

Before providing electricity to the grid, the thermal plant has to be ramped up at least to the minimum generation level, which causes the startup costs. This thesis considers the startup cost as a constant.

The solar energy cost $C_{s,t}$ includes maintenance and installation costs, which is a constant.

According to [78], the generating units constraints in deterministic unit commitment model can be written as:

$$\sum_{N_d} P_{d,t} = \sum_{N_g} p_{i,t} + \sum_{N_s} P^f_{s,t} \tag{2.4}$$

$$PG_i^{min} I_{i,t} \leq p_{i,t} \leq PG_i^{max} I_{i,t} \tag{2.5}$$

$$p_{i,t} - p_{i,t-1} \leq RU_i I_{i,t-1} + SU_i(I_{i,t} - I_{i,t-1}) + PG_i^{max}(1 - I_{i,t}) \tag{2.6}$$

$$p_{i,t-1} - p_{i,t} \leq RD_i I_{i,t} + SD_i(I_{i,t-1} - I_{i,t}) + PG_i^{max}(1 - I_{i,t-1}) \tag{2.7}$$

$$-F_l \leq \sum_{N_b} T_{l,b}\Big(\sum_{N_g(b)} p_{i,t} + \sum_{N_s(b)} P^f_{s,t} - \sum_{N_d(b)} P_{d,t}\Big) \leq F_l \tag{2.8}$$

$$\sum_{T_i^{on}} [1 - I_{i,t}] = 0 \tag{2.9}$$

$$\sum_{T_i^{off}} I_{i,t} = 0 \tag{2.10}$$

$$\sum_{h=t}^{t+T_i^u-1} I_{i,h} \geq T_i^u(I_{i,t} - I_{i,t-1}), \forall t \in [T_{i0}^{on} + 1, N_t - T_i^u + 1] \tag{2.11}$$

$$\sum_{h=t}^{N_t} [I_{i,h} - (I_{i,t} - I_{i,t-1})] \geq 0, \forall t \in [N_t - T_i^u + 2, N_t] \tag{2.12}$$

$$\sum_{h=t}^{t+T_i^d-1} (1 - I_{i,h}) \geq T_i^d(I_{i,t-1} - I_{i,t}), \forall t \in [T_{i0}^{off} + 1, N_t - T_i^d + 1] \tag{2.13}$$

$$\sum_{h=t}^{N_t} [1 - I_{i,h} - (I_{i,t-1} - I_{i,t})] \geq 0, \forall t \in [N_t - T_i^d + 2, N_t] \tag{2.14}$$

Equation (2.4) enforces the system wide power balance. Equation (2.5) describes the physical limits of the traditional generators' power output. The period-to-period startup and shut down ramping constraints are presented in equations (2.6) and (2.7). The Kirchhoff's laws are presented by equation (2.8), the elements of the power transfer distribution factors (PTDF), $T_{l,b}$, is obtained in a lossless linear DC approximation. The transmission flow constraint is shown in equation (2.8). Constraints on the initial online and offline requirements for generators are represented by equations (2.9) and (2.10). Equations (2.11) and (2.12) enforce the minimum online up-time limits for generators, including the last T_i^u time period. The minimum down-time limits in nominal time periods and last T_i^u time period for generators are shown in equations (2.13) and (2.14).

2.2.2 Real-time Dispatch

Base Case

The objective function can be formulated as

$$min \sum_{N_g} C_{g,t} \tag{2.15}$$

In base case, the traditional generators can be regulated to keep the new power balance in equation (2.16). Physical output constraints in equation (2.17) of traditional generators are also needed.

$$\sum_{N_d} P_{d,t} = \sum_{N_g} p_{i,t} + \sum_{N_s} P_{s,t} \tag{2.16}$$

$$PG_i^{min} \leq p_{i,t} \leq PG_i^{max} \tag{2.17}$$

Extreme Case

In extreme case, the proposed strategy adds the energy storage system operating costs $C_{ess,t}$ to the objective function as follows.

$$min(\sum_{N_g} C_{g,t} + \sum_{N_e} C_{e,t}) \tag{2.18}$$

Utilizing the energy power system to guarantee the system stability, extra constraints are imposed.

For the energy storage system, the following constraints are shown for the energy storage transition function in equation (2.19), and equation (2.20) sets the upper and lower energy capacity limits of the energy storage system.

$$E_{e,t} = E_{e,(t-1)} + \eta_e^C P_{e,t}^C - \frac{1}{\eta_e^D} P_{e,t}^D \tag{2.19}$$

$$E_e^{min} \leq E_{e,t} \leq E_e^{max} \tag{2.20}$$

a)Interval R2

$$\sum_{N_s} P_{s,t} + \sum_{N_g} p_{i,t} = \sum_{N_d} P_{d,t} + \sum_{N_e} P_{e,t}^C \tag{2.21}$$

$$P_e^{C,min} u_{e,t}^C \leq P_{e,t}^C \leq P_e^{C,max} u_{e,t}^C \tag{2.22}$$

The constraints in interval R1 are in the case where solar energy is higher than load demand so that energy storage system can be used to store surplus power for the economical sake. Equation (2.21) represents the new power balance and equation (2.22) describes the physical limits on the charge of the energy storage system.

b)Interval R3

$$\sum_{N_s} P_{s,t} + \sum_{N_g} p_{i,t} + \sum_{N_{ess}} P_{e,t}^D = \sum_{N_d} P_{d,t} \tag{2.23}$$

$$P_e^{D,min} u_{e,t}^D \leq P_{e,t}^D \leq P_e^{D,max} u_{e,t}^D \tag{2.24}$$

In interval R3, the extreme case is used when solar energy is lower than load demand. The energy storage system is regulated to discharge the sufficient power and inject the discharging power to the power system for power balance as presented in equation (2.23). Equation (2.24) limits the energy storage system charge physical ability.

For the whole extreme cases (R2+R3), the status constraint of energy power system can be described by the following equation

$$u_{e,t}^{C} + u_{e,t}^{D} \leq 1 \tag{2.25}$$

2.3 Algorithm Framework

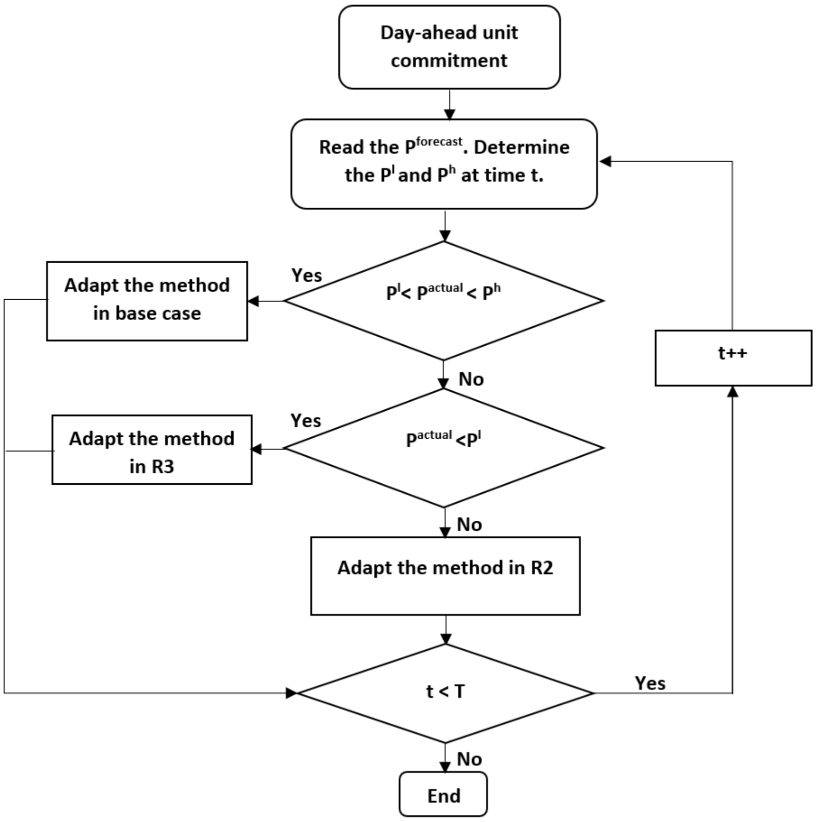

Figure 2.3.1: Flowchart of the proposed unit commitment model

The proposed model to solve the hourly energy storage system dispatch problem is divided into two subproblems shown as in Figure 2.3.1.

The algorithm for handling the variation of forecasted solar power output problem and dispatching the energy storage system can be summarized as follows.

Step 1. Make the forecast on day-ahead hourly solar power output and load demand. Calculate the confidence interval of solar power output at each time interval. Determine the initial state of traditional generators and energy storage system by day-ahead unit commitment.

Step 2. Compare the actual solar power output with the lower and upper confidence bounds of forecasted solar power output and determine the type of case to coordinate the power balance of whole network system. Base case can solve the variation of solar power output in confidence interval. Case R2 can solve the problem that actual solar power output is greater than the forecasted, and case R3 enables the energy storage system to keep power balance when the actual solar power output is less than the forecasted solar power output.

Step 3. Update the state of traditional generators and energy storage system.

Step 4. If t is the last time interval, stop; otherwise, go to step 2.

2.4 Case Studies

This section presents the parameters for testing power system and solar power output, and the results of simulation studies. In addition, the algorithm is compared with an existing one from the literature.

2.4.1 Simulation Preconditions

In this section, a case study is conducted based on IEEE 14-bus test system as shown in Figure 2.4.1. The test system is composed of 4 traditional generators, 14 buses, 20 transmission lines and 11 load points and its data is given by [1]. The cost coefficients of traditional generators are shown in Table 2.1 [79]. A 30MW PV installation with 50MW storage system are connected to the bus 8. The characteristic of energy storage system is shown in Table 2.2. The initial stored power of the energy storage system is considered to be 35MW. Details about test system including PV generation are in *Appendix A.1*.

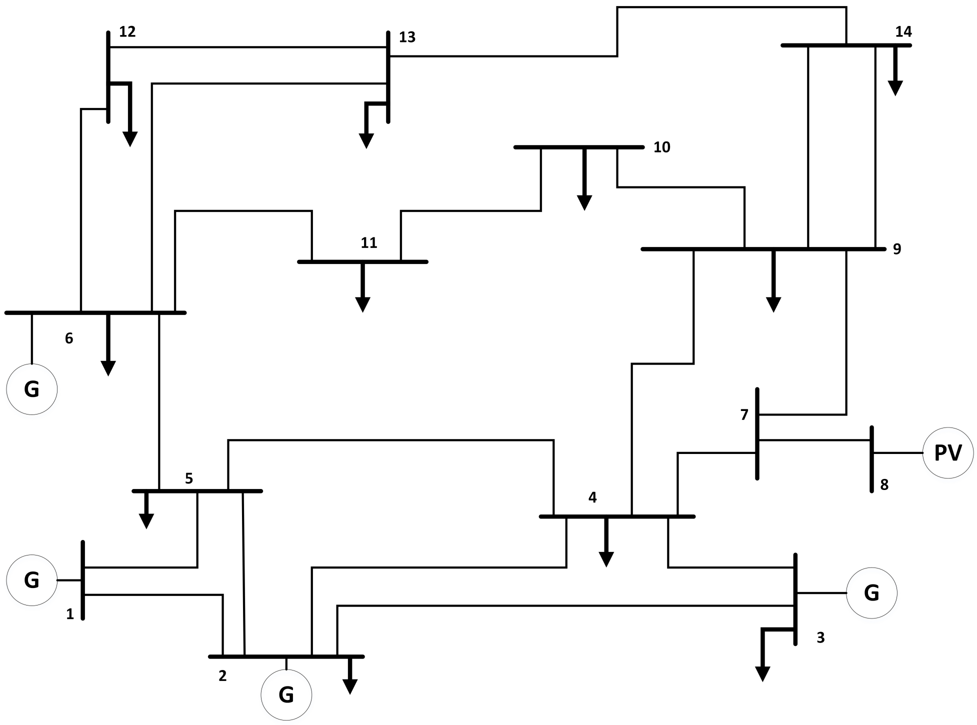

Figure 2.4.1: IEEE 14-bus test system

Table 2.1: Traditional generators parameters

Unit	Cost Coefficients			Start up Costs
	a	b	c	
1	0.00315	2.0	0	70
2	0.01750	1.75	0	74
3	0.06250	1.0	0	50
4	0.00834	3.25	0	110

The probability model of solar power output is assumed to follow a normal distribution (Norm(μ,σ^2)). The average (μ) is the forecasted generated power $P^{forecast}$ at each time and the standard deviation (σ) is 0.05 as shown in Figure 2.2.1.

A simulation for a reference case (RC) [3], where ESS is regulated in hourly dispatch with a deterministic day-ahead unit commitment model, is performed to

Table 2.2: Energy storage system parameters

Capacity(MWh)	Power(MW)	Efficiency	Cost
50	10	0.85	2.0

show the effectiveness of the proposed model. The details of the model formulation are in *Appendix B.1*.

The confidence level $(1-\alpha)$ is set as 95%.

The proposed UC model is solved by CPLEX 12.7 on a personal computer with 2.5-GHz CPU and 12GB RAM.

This thesis obtains solar power output from Belgium's electricity transmission system operator Elia [81], of which location is Luxembourg. Case A and Case B are simulated to show the effectiveness of proposed strategy. Figure 2.4.2 and Figure 2.4.3 show the comparison of forecasted and actual solar power output in case A and case B, separately.

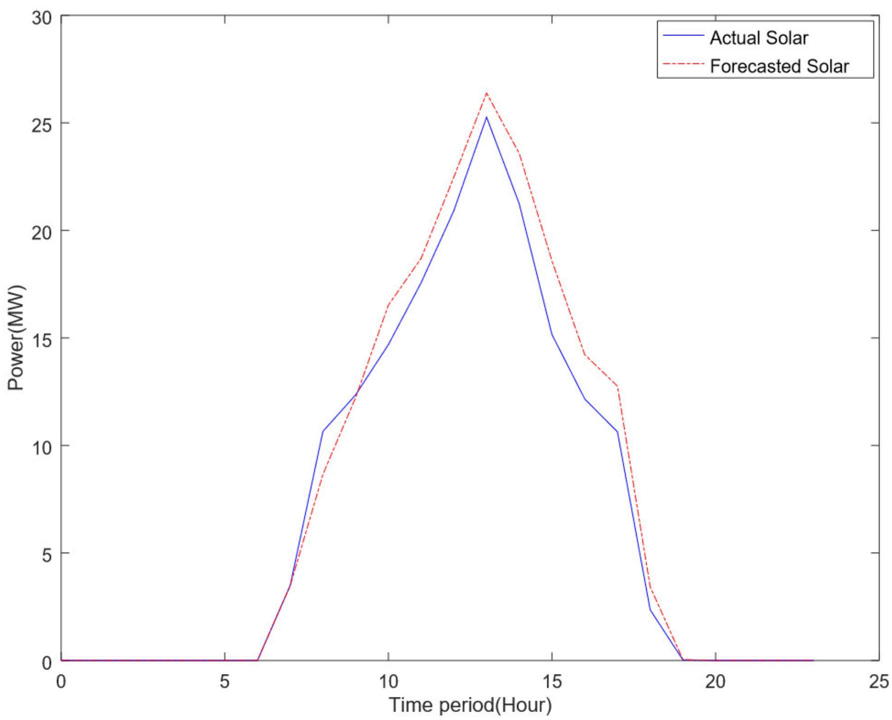

Figure 2.4.2: Case A: actual vs forecasted solar power output

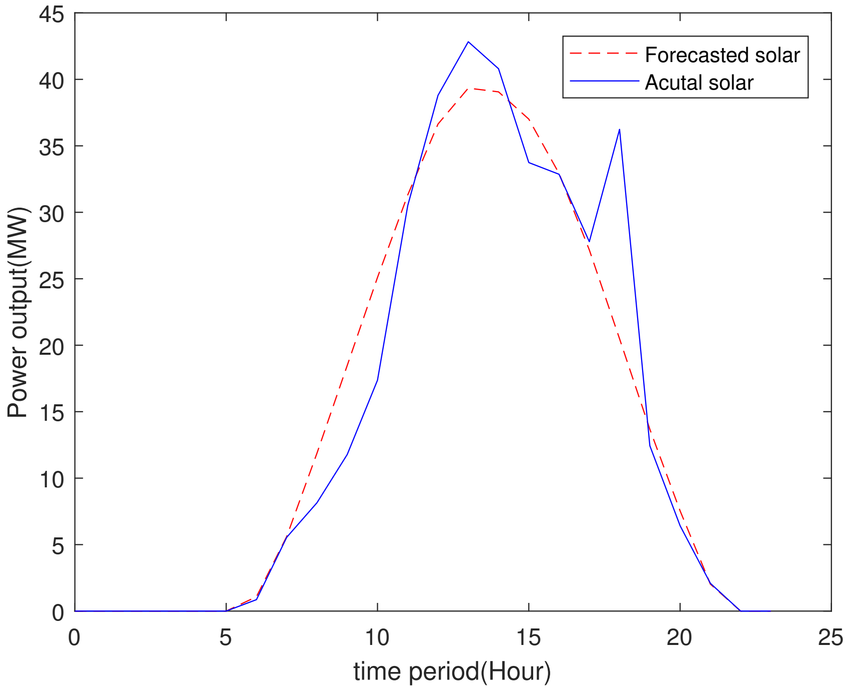

Figure 2.4.3: Case B: actual vs forecasted solar power output

2.4.2 Simulation Results

The minimization of operation cost is the objective for all optimize problems in power system to obtain a more economical schedule. As the consideration of energy storage system is to help the power system run steady, fast and accurate calculation to the changes of solar power output is vital. Therefore, our results focus on two main aspects: the handling time and the total operation cost.

Handling Time

Table 2.3: Case A: comparison of the handling time in whole day:RC and proposed UC

Case	Average handling time (in /1000 sec)
Reference case	160
Proposed UC	91

Table 2.4: Case B: comparison of the handling time in whole day:RC and proposed UC

Case	Average handling time (in /1000 sec)
Reference case	140
Proposed UC	92

From Table 2.3 and Table 2.4, the average handling time of the proposed UC is shorter than the RC. This means that the proposed UC model effectively reduces the computational complexity.

Operation Cost

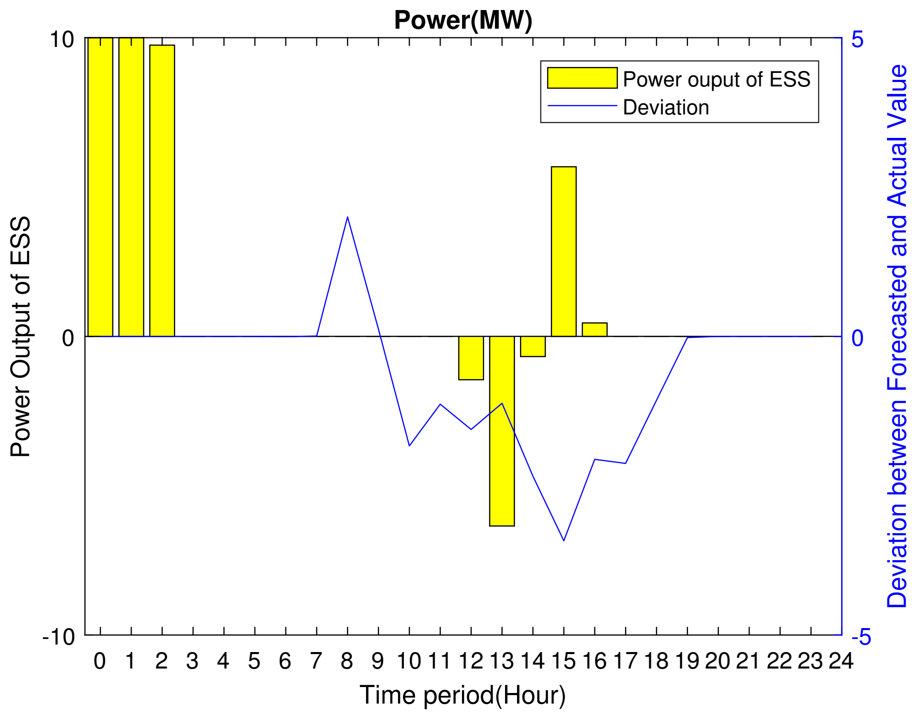

Figure 2.4.4: Case A: power output of ESS with deviation in RC

Figure 2.4.4 and Figure 2.4.5 show the combination with power output from energy storage system with the deviation between forecasted and actual solar power output for each time period in RC and the proposed model, respectively.

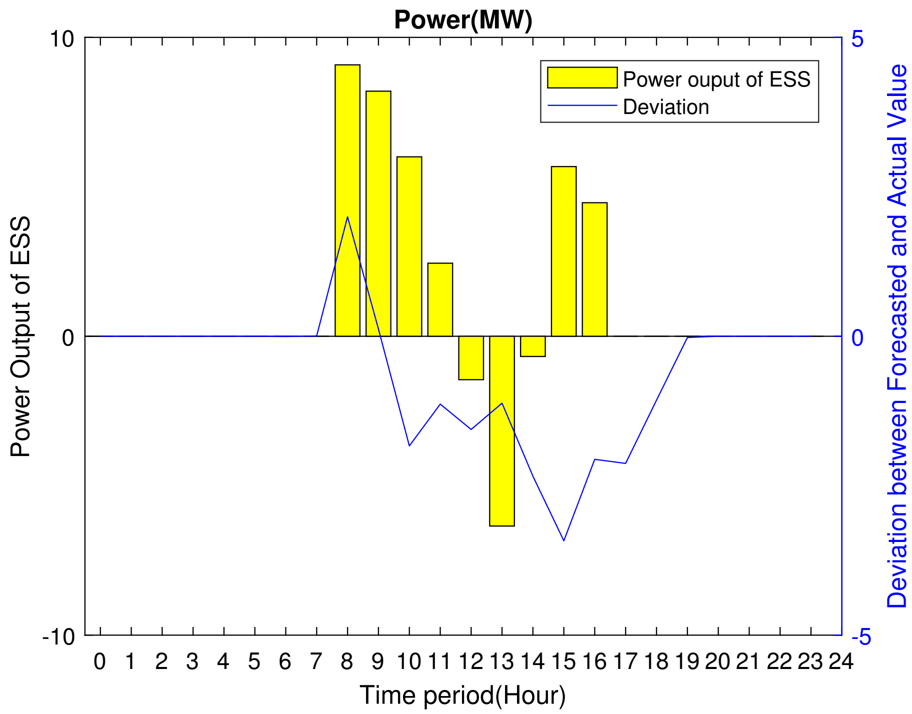

Figure 2.4.5: Case A: power output of ESS with deviation in the proposed model

The yellow block represents that the energy storage system discharge stored power or charge surplus power from power system to balance the whole system power. Some observations on the commitment of energy storage system are made. Energy storage system is committed when there appears the deviation of solar power output in the proposed strategy, while the commitment of energy storage system is made at the beginning of the whole day where there is no deviation.

In addition, from Table 2.5 and Table 2.6, the total operation cost of the proposed UC is smaller than the RC.

Table 2.5: Case A: comparison of the total operation costs:RC and proposed UC

Case	Operation Cost
Reference case	11688
Proposed UC	11681

Table 2.6: Case B: comparison of the total operation costs:RC and proposed UC

Case	Operation Cost
Reference case	11070
Proposed UC	11065

2.5 Conclusion

In this chapter, in order to be adaptive to the change of solar irradiance which is closely related to the solar generation quantity, we proposed an hourly energy storage system dispatch model to supplement and improve the day-ahead unit commitment which is on the basis of the forecasted solar power output. The proposed model is divided into two main cases according to the two intervals of solar power output probability distribution. In addition, energy storage system is coordinated when the deviation of solar power output is larger than the confidence interval to help the power system run safely and steadily.

The simulation results reveal the effectiveness of the proposed UC model to deal with the uncertainty of solar generation output. It shortens the computation time effectively and reduces the total operation cost, as well as a more flexible control in the face of the deviation of solar power output. The acceleration of operation can reduce the calculative burden, which is more practical. The operation cost reduction meets the economical requirement.

Chapter 3

Unit Commitment with Solar Resource and Uncertainty Load

This chapter presents the proposed UC model considering both uncertain solar resource and load demand. The energy system model is given in *Section 3.1*, and the proposed UC model is presented in *Section 3.2*. In *Section 3.2*, the main results are presented. The proposed scheduling strategy is implemented on a modified IEEE 30-bus solar resource integrated test system in *Section 3.4*. In addition, this thesis summarizes the work mentioned previously and draw conclusions on results obtained in *Section 3.5*.

3.1 Energy System Model

3.1.1 Uncertain Solar Model

The method adopted in this chapter uses historical solar radiation data to forecast solar power output. In order to collect forecast solar radiation data and generate scenario sets, the mathematical model takes into account the difference among the solar radiation in different intervals and initial samples scheme from a multivariate distribution. As in the last chapter, it is assumed that the probabilistic model of the PV power output approximates a normal distribution model $N(\mu, {\sigma_1}^2)$ for simplicity as shown in Figure 3.1.1, where the average μ_1 is the forecasted solar power output $P_{s,t}^f$ and the variance ${\sigma_1}^2$ is deduced by weather and geographic factors.

3.1.2 Uncertain Net Load

Most earlier work uses the single point estimation for hourly load demand, which is actually inaccurate, and puts it into the deterministic formulation. In [75], the normal distribution is assumed for load components with a standard deviation accounting for the forecast errors. Thus this chapter uses a hierarchical unit commitment model assuming that the hourly loads follow a normal distribution $N_d(\mu_2, {\sigma_2}^2)$ with the corresponding mean is forecasted hourly load demand $P_{d,t}^f$ and variance is deduced by forecast errors.

According to the characteristic functions of independent normal distribution, the net load $P_{net,t}^f$, as shown in equation (3.1), is also normally distributed $N_{net}(\mu_2 - \mu_1, {\sigma_2}^2 - {\sigma_1}^2)$, with its mean being the subtraction of the two means, and its variance being the subtraction of the two variances:

$$P_{net,t}^f = P_{d,t}^f - P_{s,t}^f \tag{3.1}$$

From equation (3.1), we consider solar power output as injection load at the bus. Therefore, the uncertain solar power output and uncertain load demand can be combined to uncertain net load demand, which simplifies the whole optimization.

3.1.3 Ideal and Generic Energy Storage System

This thesis defines a generic energy storage system as the device that is able to transform and store energy. In this chapter, the function of the ideal and generic energy storage system is to compensate for the inaccuracy of forecasting by ab-

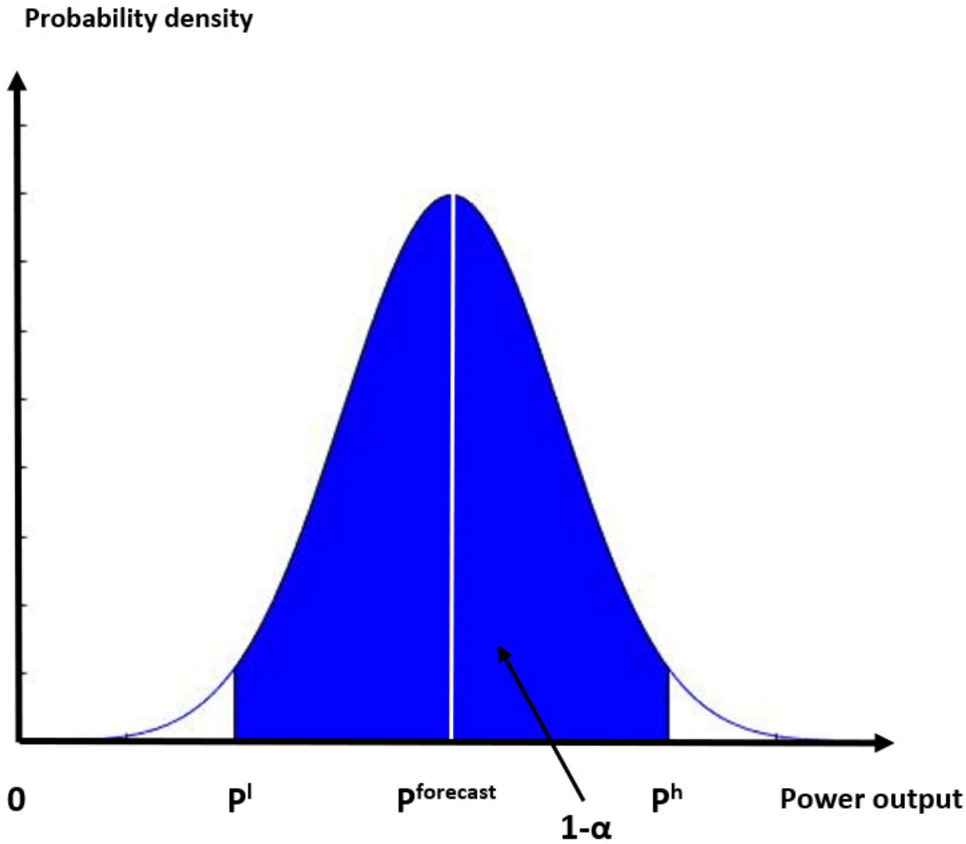

Figure 3.1.1: Probability distribution of power output

sorbing the surplus energy from the system and injecting back the stored energy to the system. This thesis assume the ideal energy storage system has certain simplifications about its operation and costing. It can by modeled [3] by equation (3.2), (3.3)and (3.4). Equation (3.2) shows the energy storage system transition function and equation (3.3) sets the upper and lower energy capacity limits of the energy storage system. The status constraints of energy power system are described in equation (3.4).

$$E_{e,t} = E_{e,(t-1)} + \eta_e^C P_{e,t}^C - \frac{1}{\eta_e^D} P_{e,t}^D \tag{3.2}$$

$$E_e^{min} \leq E_{e,t} \leq E_e^{max} \tag{3.3}$$

$$u_{e,t}^C + u_{e,t}^D \leq 1 \tag{3.4}$$

Then, some assumptions on the ideal and generic energy storage system are listed as follows:.

1) There are no losses, such as stored energy losses and conversion losses. The former means that the energy stored can be seen as a constant if there is no energy conversion. The latter means that only transfer efficiency rate is considered in the energy transformation.

2) There is no hysteresis in energy transformation, including charging and discharging. Power output of a unit can be acquired instantly.

3) The energy conversion occurs for the certain period (the period is one hour in this chapter).

3.2 Proposed Methodology

This section introduces the proposed scheduling strategy.

3.2.1 Unit Commitment Model

Objective Function

$$min \sum_{N_t} (\sum_{N_g} C_{g,t} + \sum_{N_e} C_{e,t}) \tag{3.5}$$

The objective function is formulated as equation (3.5) to minimize the operating cost which is consisted of traditional generator costs $C_{g,t}$ and energy storage costs $C_{e,t}$. The solar cost is considered to be installation and maintenance fee which is a constant, so that it can be assumed to be zero in this formulation.

The traditional generator costs contains fuel costs $F_i(p_{i,t})$ and startup costs $ST_i(u_i)$, as shown in equation (3.6).

$$C_{g,t} = F_i(p_{i,t}) + ST_i(u_i) \tag{3.6}$$

The fuel cost function $F_i(p_{i,t})$ [42] is assumed to be quadratic as shown in equation (3.7). a_i, b_i and c_i are the coefficients of each traditional generator fuel cost function.

$$F_i(p_{i,t}) = a_i p_{i,t}^2 + b_i p_{i,t} + c_i \tag{3.7}$$

Constraints

$$\sum_{N_d} P_{d,t} = \sum_{N_g} p_{i,t} + \sum_{N_s} P_{s,t} \tag{3.8}$$

$$PG_i^{min} I_{i,t} \leq p_{i,t} \leq PG_i^{max} I_{i,t} \tag{3.9}$$

$$p_{i,t} - p_{i,t-1} \leq RU_i I_{i,t-1} + SU_i(I_{i,t} - I_{i,t-1}) + PG_i^{max}(1 - I_{i,t}) \tag{3.10}$$

$$p_{i,t-1} - p_{i,t} \leq RD_i I_{i,t} + SD_i(I_{i,t-1} - I_{i,t}) + PG_i^{max}(1 - I_{i,t-1}) \tag{3.11}$$

$$-F_l \leq \sum_{N_b} T_{l,b}(\sum_{N_g(b)} p_{i,t} + \sum_{N_s(b)} P_{s,t} - \sum_{N_d(b)} P_{d,t}) \leq F_l \tag{3.12}$$

$$\sum_{T_i^{on}} [1 - I_{i,t}] = 0 \tag{3.13}$$

$$\sum_{T_i^{off}} I_{i,t} = 0 \tag{3.14}$$

$$\sum_{h=t}^{t+T_i^u-1} I_{i,h} \geq T_i^u(I_{i,t} - I_{i,t-1}), \forall t \in [T_{i0}^{on} + 1, N_t - T_i^u + 1] \tag{3.15}$$

$$\sum_{h=t}^{N_t} [I_{i,h} - (I_{i,t} - I_{i,t-1})] \geq 0, \forall t \in [N_t - T_i^u + 2, N_t] \tag{3.16}$$

$$\sum_{h=t}^{t+T_i^d-1} (1 - I_{i,h}) \geq T_i^d(I_{i,t-1} - I_{i,t}), \forall t \in [T_{i0}^{off} + 1, N_t - T_i^d + 1] \tag{3.17}$$

$$\sum_{h=t}^{N_t} [1 - I_{i,h} - (I_{i,t-1} - I_{i,t})] \geq 0, \forall t \in [N_t - T_i^d + 2, N_t] \tag{3.18}$$

According to [78], equation (3.8) enforces the system wide power balance. Equation (3.9) describes the physical limits of the traditional generators' power output. The period-to-period startup and shut down ramping constraints are presented in equations (3.10) and (3.11). The Kirchhoff's laws are presented by equation (3.9), the elements of the power transfer distribution factors (PTDF), $T_{l,b}$, is obtained in a lossless linear DC approximation. Constraints on the initial online and offline requirements for generators are represented by equations (3.13) and (3.14). Equations (3.15) and (3.16) enforce the minimum online up-time limits for generators, including the last T_i^u time period. The minimum down-time limits in nominal time periods and last T_i^u time period for generators are shown in equations (3.17) and (3.18).

3.2.2 Hierarchical Scheduling Strategy

Due to the uncertainty of solar power and load demand, this chapter adopts the forecast method as mentioned to acquire the hourly expected value of solar power output and load demand.

Based on equation (3.1), define the minimum and maximum of net load demand as 0 and P_{net}^{max}, respectively. This means that the net load demand range is $[0, P_{net}^{max}]$ at each scheduled period.

Considering the energy storage system coordination, the proposed hierarchical scheduling strategy divides the value of net load demand range into two intervals at each scheduled period, which correspond to confidence interval and non-confidence interval based on the confidence level $(1-\alpha)$ for probabilistic interval model, as shown in Figure 3.2.1.

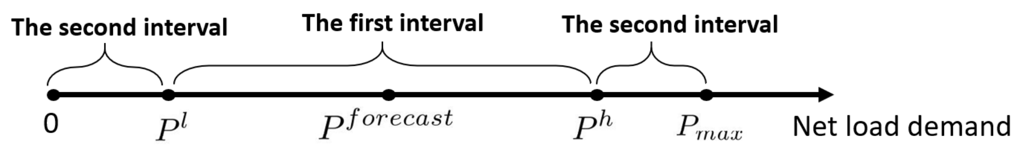

Figure 3.2.1: Interval partition of net load demand

The First Interval

As shown in Figure 3.1.1, in this interval, net load demand has a significant probability which actually falls into $[P_{net}^l, P_{net}^h]$. All traditional generators are committed to respond to uncertain net load demand. The constraints in the first interval are the power balance, traditional generators physical constraints and transmission constraints, which can be described by equations (3.8) to (3.18).

The Second Interval

Net load demand might occur in this interval, where the forecast error is relatively large. Energy storage system is dispatched to satisfy the power system security. Therefore, constraints in this interval are energy storage system physical constraints in equations (3.2) to (3.4) and charged/discharege power of energy storage system in equation (3.19). ΔP_{net} is the difference between the actual net load and the endpoint of expected net load, which is determined in dispatch.

$$\sum_{N_e} P_e = \Delta P_{net} \tag{3.19}$$

3.3 Solution of Hierarchical Scheduling

In this section, different solutions in different intervals are utilized to simplify the formulation.

3.3.1 Solution for First Interval

The formulation in the first interval is a large-scale, mixed-integer problem and is very difficult to solve directly due to the complexity and the additional computational burden. To avoid this computational intractability, this problem needs to be divided into master problem and subproblems and solved in different conditions.

The master problem only takes the forecasted value of net load demand into account, in other words, master problem is a standard unit commitment problem. The subproblem is solved with confidence interval which considers many scenarios in the interval and is hard to figure out due to its complexity. In the following, we will introduce the decomposition of the unit commitment problem in details.

Decomposition of Unit Commitment

As mentioned earlier, the aim of the master unit commitment problem is to acquire the optimal unit commitment solution under forecasted net load $P^f_{net,t}$. For other possible scenarios in confidence interval, the solution of master unit commitment should also be feasible. And the expected power balance is presented by equation (3.20) with traditional generator physical constraints.

$$\sum_{N_b} P^f_{net,t} = \sum_{N_g} p_{i,t} \tag{3.20}$$

The subproblem is to check the feasibility of the result of the master unit commitment by substituting the on/off states into a series of equivalent economic dispatch problem for each net load scenario, as shown in equation (3.21).

$$\sum_{N_b} P^s_{net,t} = \sum_{N_g} p_{i,t} \tag{3.21}$$

The resulting on/off state $i_{i,t}$ will be checked in subproblem to improve the master unit commitment problem.

The subproblem takes the resulting on/off state $i_{i,t}$ into economic dispatch problem for possible scenarios to improve the result.

However, as mentioned above, the possible scenarios are numerous, and cannot be solved directly. Confidence interval for $P^f_{net,t}$ is utilized to simplify the formulation.

Simplification for Subproblem

Among lots of possible scenarios, some representative critical scenarios could be found out, and the feasible solution for all possible scenarios could be obtained by checking only these critical ones. These critical scenarios are defined as the extreme-case to meet the requirement of simplifying the formulation.

From the unit commitment model, power balance and transmission constraints take the uncertain net load demand into account and they are in linear programming problem where the extreme cases are at the endpoints of interval [77] [80], which means that the solution of the subproblem should focus on their simplification. Shown in Figure 3.1.1, the lower and upper bound of the first interval are two endpoints of confidence interval, P^l_{net} and P^h_{net}. These two constraints can be explicitly expressed as equation (3.22) and (3.23) [71].

$$\sum_{N_b}[P^l_{net,t}, P^h_{net,t}] = \sum_{N_g} p_{i,t} \tag{3.22}$$

$$-F_l \leq \sum_{N_b} T_{l,b}(\sum_{N_g(b)} p_{i,t} - \sum_{N_b}[P^l_{net,t}, P^h_{net,t}]) \leq F_l \tag{3.23}$$

Equation (3.22) can be transformed into equation (3.24a) and (3.24b) [71].

$$\sum_{N_b} P^l_{net,t} = \sum_{N_g} p^l_{i,t} \tag{3.24a}$$

$$\sum_{N_b} P^h_{net,t} = \sum_{N_g} p^h_{i,t} \tag{3.24b}$$

Equation (3.23) can be transformed into equation (3.25a) and (3.25b) [71].

$$\sum_{N_b} T_{l,b} p_{i,t} \geq -F_l + \sum_{N_b} T_{l,b}[P^l_{net,t}, P^h_{net,t}] \tag{3.25a}$$

$$\sum_{N_b} T_{l,b} p_{i,t} \leq F_l + \sum_{N_b} T_{l,b}[P^l_{net,t}, P^h_{net,t}] \tag{3.25b}$$

In transmission constraints, F_l and $T_{l,b}$ are constants. This thesis define $\sum\limits_{N_b} T_{l,b}[P_{net,t}^l, P_{net,t}^h]$ also has its certain range $[TP^l, TP^h]$. The term $T_{l,b}P_{net,t}^l$ is the maximum value when $T_{l,b} < 0$ and is the minimum value when $T_{l,b} > 0$, the term $T_{l,b}P_{net,t}^h$ presents otherwise.

The extreme cases occur when equation (3.25a) and (3.25b) reach their limits on the right sides as follows

$$\sum_{N_b} T_{l,b}p_{i,t}^h \geq -F_l + TP^h \tag{3.26a}$$

$$\sum_{N_b} T_{l,b}p_{i,t}^l \leq F_l + TP^l \tag{3.26b}$$

These simplification substantially reduces computational complexity for uncertain net load.

Therefore, the original constraints (3.8) and (3.12) with large number of scenarios is simplified in equation (3.24a), (3.24b), (3.26a) and (3.26b) without loss of optimality.

3.3.2 Solution for Second Interval

In second interval, energy storage system is coordinated to guarantee the net load demand ranges in the acceptable range so that solution of the first interval can satisfy the net load demand with volatility.

The cost function of energy storage system adopted is a linear function as shown in equation (3.27). P_e represents its discharged power and the negative value represents the charged power, as presented by equation (3.28). New transmission constraints in equation (3.29) is needed.

$$C_e = \lambda P_e \tag{3.27}$$

$$\begin{aligned} P_e &= P_e^D \\ P_e &= -P_e^C \end{aligned} \tag{3.28}$$

$$-F_l \leq \sum_{N_b} T_{l,b}(\sum_{N_g(b)} p_{i,t} + \sum_{N_e(b)} P_{e,t} - \sum_{N_b} P_{net,t}) \leq F_l \tag{3.29}$$

3.3.3 Framework of Hierarchical Strategy

The hierarchical unit commitment is divided into two intervals according to the definition of confidence interval as shown in Figure 3.3.1.

The algorithm for handling the deviation of forecasted value problem and dispatching the energy storage system can be summarized as follows.

Step 1. Make the forecast value on day-ahead hourly solar power output and load demand. Calculate the forecasted net load demand and its confidence interval at each time interval. Determine the initial state of traditional generators and energy storage system by day-ahead unit commitment.

Step 2. The master problem in the first interval where net load demand is expected value. Extra constraints for endpoint of confidence interval are added to guarantee that the resulting state of master problem can meet the security requirement of power system for different net load demand in the confidence interval, which is used to improve the result of master problem for day-ahead unit commitment.

Step 3. Compare the actual value with the endpoints of forecasted confidence interval. Day-ahead resulting states of generators can accommodate the real net load demand which is in the confidence interval. Energy storage system is committed to guarantee the schedule result in the first interval is able to keep wide power balance with different net load demand in the low probability interval in hourly dispatch.

Step 4. Update the state of traditional generators and energy storage system.

Step 5. If t is the last time interval, stop; otherwise, go to step 3.

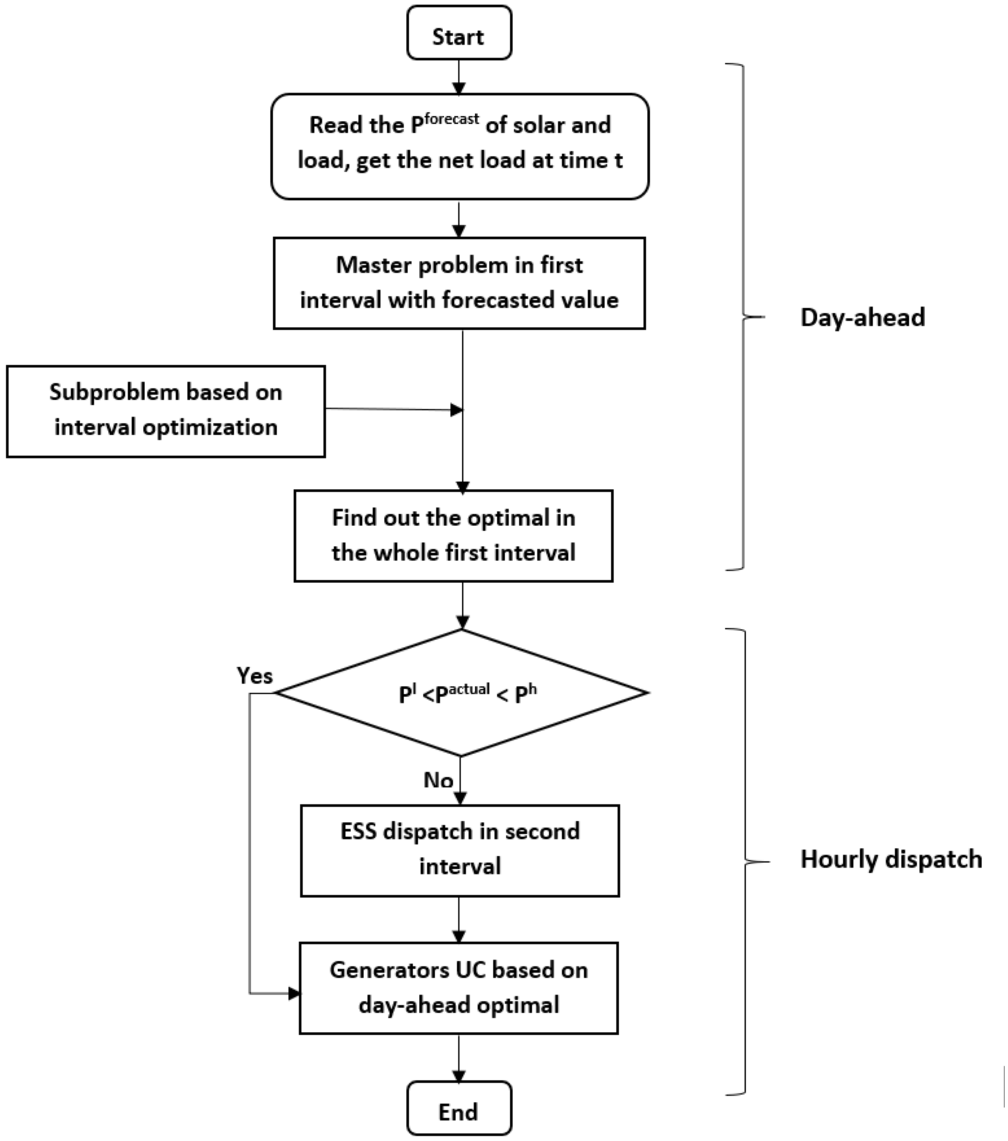

Figure 3.3.1: Flowchart of hierarchical unit commitment

3.4 Case Studies

In order to focus on uncertain net load, this thesis assumes that other faults, including N-1 contingency and outage in traditional generators, even break down in system will not occur in our simulation. That means this thesis only studies the violation of solar resource and load demand.

In this section, we present the details of testing power system, uncertain solar resource and load demand. The simulation results of proposed strategy and reference case are given and analysis on the algorithm is provided.

3.4.1 Simulation System

The test system is a modified IEEE 30-bus system as shown in Figure 3.4.1, which has 5 traditional generators, 41 transmission lines and 20 load demand points. The system network parameters are given by [2]. The cost coefficients of traditional generators are shown in Table 3.1. Two solar resources with energy storage system are located at bus 13 and 27, which are from a summer day data from Belgium's electricity transmission system operator Elia [81], and their selection are Luxembourg and Brussels, separately. The two energy storage systems have the capacity of 50MW and 40MW, individually. Their characteristic parameters in the case study are presented in Table 3.2. The initial stored power of two energy storage systems are 30MW and 20MW, respectively.

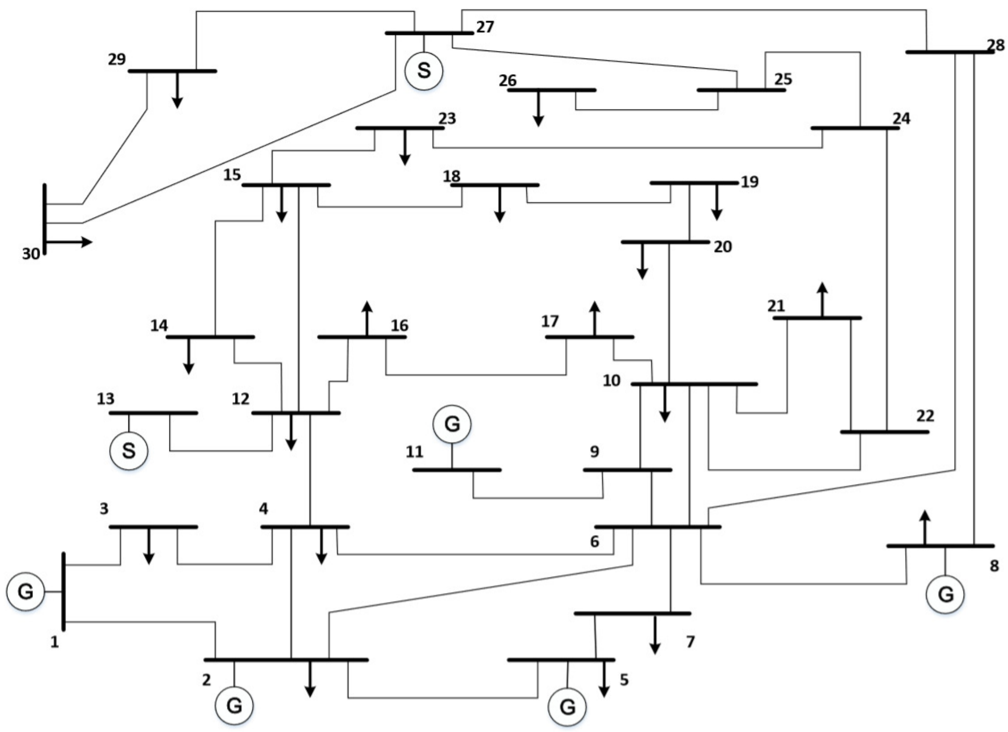

Figure 3.4.1: IEEE 30-bus test system

Table 3.1: Traditional generators parameters

Unit	Cost Coefficients			Start up Costs
	a	b	c	
1	0.00315	2.00	0	70
2	0.01750	1.75	0	74
3	0.06250	1.00	0	110
4	0.00834	3.25	0	50
5	0.02500	3.00	0	72

Table 3.2: Energy storage system parameters

Power(MW)	Efficiency	Cost
10	0.85	2.5

The probability model of net load demand is assumed to be a difference between load demand and solar resource, given by equation (3.1), which also follows a normal distribution $N_{net}(\mu_{net}, {\sigma_{net}}^2)$. The average μ_{net} is the forecasted net load demand $P_{net}^{forecast}$ at each time and the square of the variance ${\sigma_{net}}^2$ is 6.0 as shown in Figure 3.1.1. And Figure 3.4.2 shows the actual and forecasted net load demand.

The confidence level $(1-\alpha)$ in this case is set as 95%.

All simulations of different model are carried out by CPLEX 12.6 on a personal computer with 3.7-GHz CPU and 16GB RAM.

3.4.2 Simulation Results

Due to the aim and structure of the proposed model, the effectiveness of proposed model is shown in two parts: day-ahead part and hourly-ahead part.

1) For day-ahead part, we compare our results with reference case (RC) on the generation capacity, which is the ability to guarantee system security by satisfying the volatility of solar resource and load demand. Therefore, the reference case [4] in day-ahead part is a deterministic day-ahead unit commitment with energy

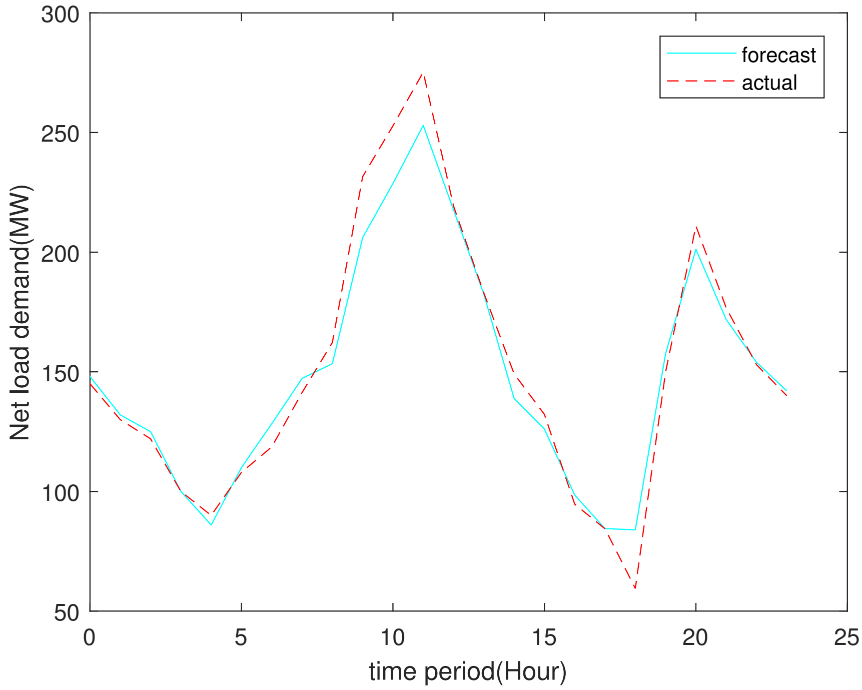

Figure 3.4.2: Actual vs forecasted net load demand

storage system under forecasted value of solar resource and load demand. The details of model formulation are shown in *Appendix B.2*.

2) For hourly-ahead part, energy storage system is dispatched to attain the goal of its regulation performance and economy. The effectiveness thus includes handling time and operation cost. And the reference case [3] is a deterministic hourly-ahead unit commitment with energy storage system under actual value of solar resource and load demand. The details of the model formulation are given in *Appendix B.1*.

Generation Capacity

This section focuses on the generation capacity of power system, in other words, there is no power loss, such as transmission congestion, voltage loss and equipment loss. Power generated from traditional generators and discharged or absorbed from energy storage system can be delivered to load demand without any loss.

Reference case model is a day-ahead model which is solved by using predicted net load demand. Its energy storage system is committed for the objective function of minimizing the operation cost. The details are given in the Appendix.

The comparison of generation capacity for resulting states for generators between proposed model and reference case model is shown in Figure 3.4.3. Each model has the maximum and minimum power generation owing to physical power output constraints of traditional generators.

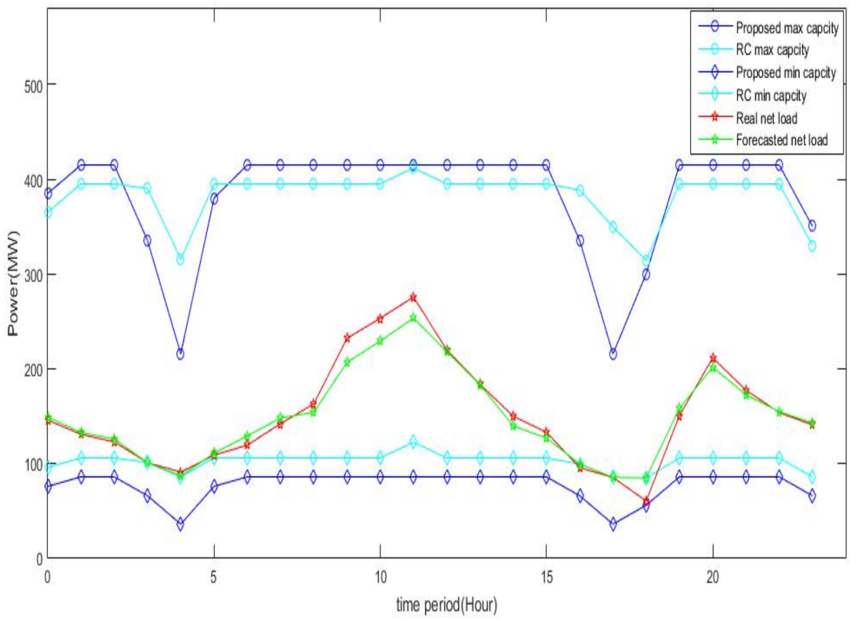

Figure 3.4.3: Comparison of the power generation capacity

Figure 3.4.3 shows that each model can satisfy the forecasted net load demand. However, some problems occur in the real net load demand condition. During the time period t=16,17 and 18, the minimum power generation capacity of reference case model is larger than real net load demand and the power system suffers the power imbalance, which causes the power system stability. And the proposed model satisfies the net load demand in the whole day.

Therefore, the proposed model is more flexible to uncertain solar resource and load demand with volatility, which enhances the stability of power system.

Handling time

From Table 3.3, the average handling time of our proposed UC is shorter than the RC. Thus, the proposed model effectively reduces the computational complexity.

Table 3.3: Comparison of the handling time in whole day:RC and proposed UC

Case	Average handling time (in /1000 sec)
Reference case	162
Proposed UC	75

Operation Cost

From Table 3.4, the total operation cost of the proposed UC is smaller than the RC. It is clear that the proposed model is effective for saving operation cost, which is the main aim for all unit commitment models.

Table 3.4: Comparison of the total operation costs:RC and proposed UC

Case	Operation Cost
Reference case	10150.0
Proposed UC	9717.3

Figure 3.4.4 and Figure 3.4.5 show the commitment of energy storage system in different models. Different color blocks represent that the energy storage system discharges of charge power which satisfy uncertain net load demand. Blue line is the difference between forecasted and actual value of net load demand. Some observations can be made. In the proposed model, energy storage systems are dispatched when the difference becomes larger. when the actual value

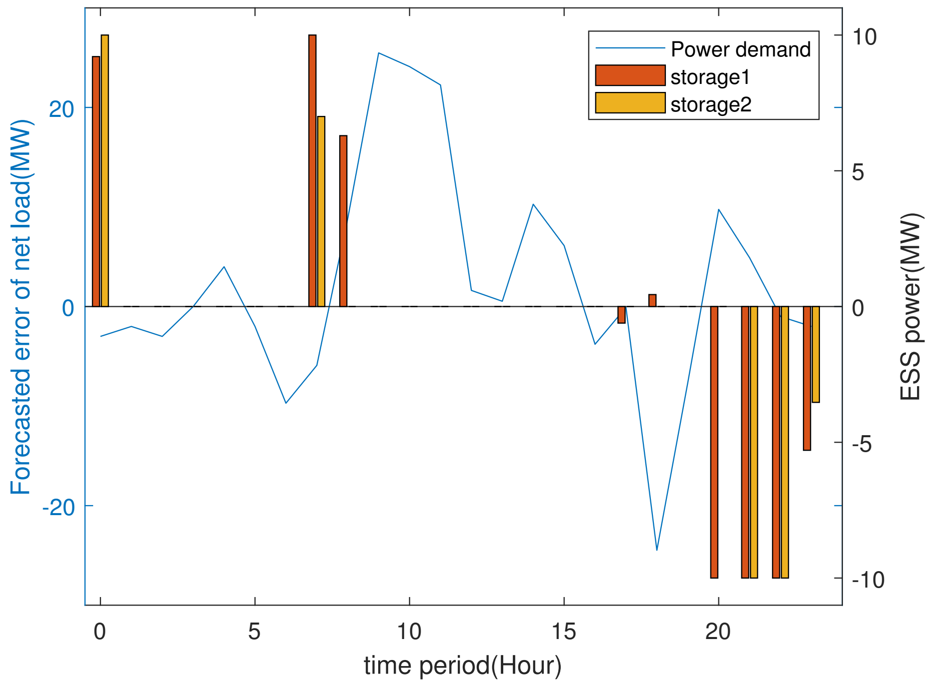

Figure 3.4.4: ESS power output in hourly-ahead RC model

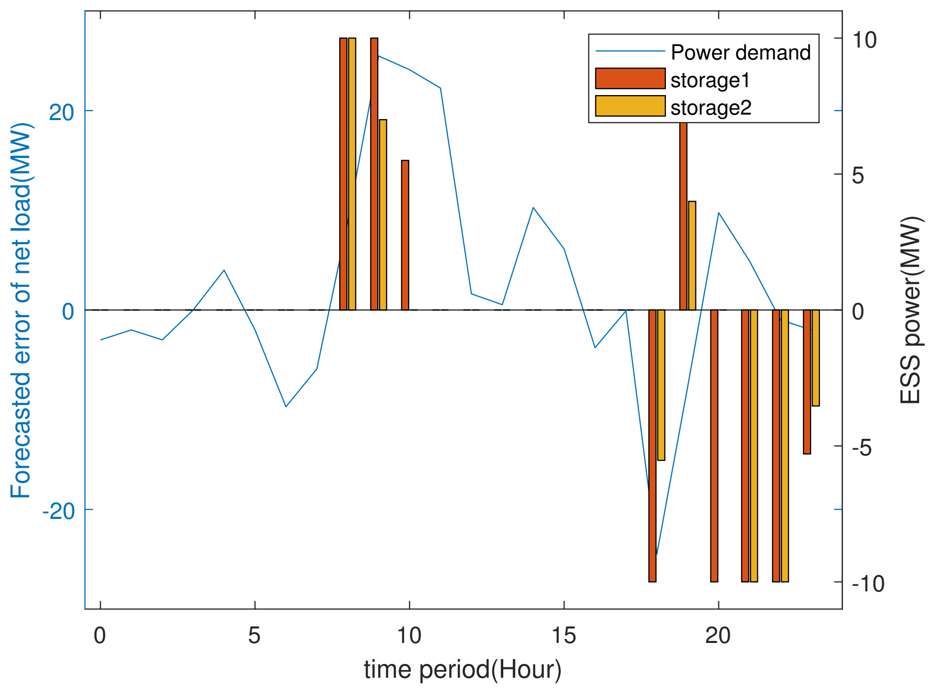

Figure 3.4.5: ESS power output in proposed model

is larger than forecasted value, energy storage systems are regulated to absorb surplus power from power system, and inject the insufficient power to system as the actual value is smaller than forecasted value, which realizes the function of the energy storage system. While the hourly-ahead RC does not commit energy storage system by following the error of forecasted net load demand. For last 4 hours, energy storage systems charge power to achieve the goal of turning back the initial state and prepare for the next day's schedule, as shown in Figure 3.4.6 and Figure 3.4.7.

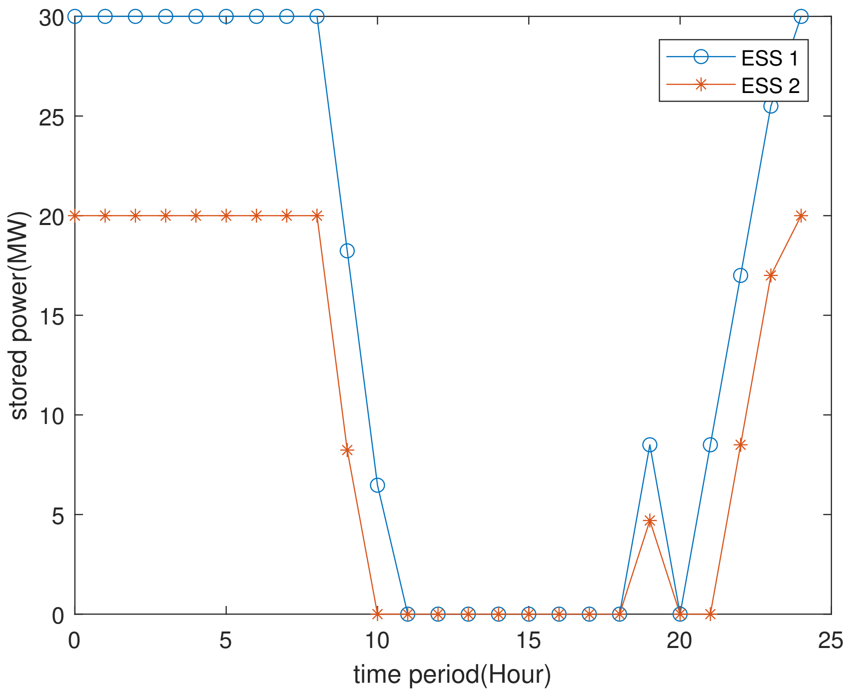

Figure 3.4.6: State of ESS in hourly-ahead RC model

3.5 Conclusion

This chapter considers both solar resource and load demand. In deterministic unit commitment model, load demand is regarded as a constant which in reality

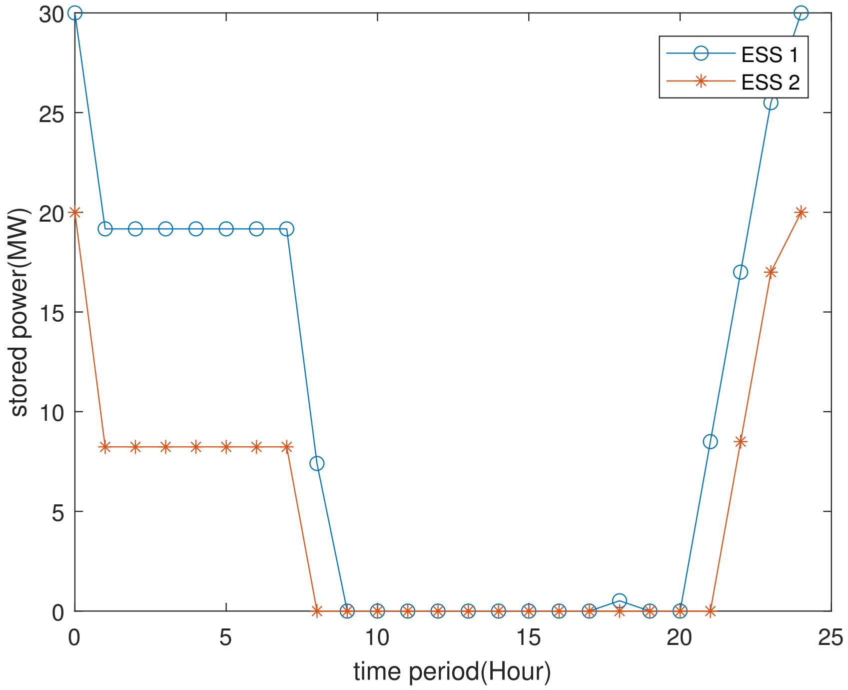

Figure 3.4.7: State of ESS in proposed model

is volatile. Solar resource is a resource with uncertainties. Based on this observation, motivated from [74] and [75], we model two kinds of uncertainties as a probability distribution. Based on the probability theory of normal distribution, two independent normal distributions can form a new normal distribution, which is defined as net load demand. Similar to that in the last chapter, the net load demand range is divided into two intervals, namely, the confidence interval and the non-confidence interval. Net load demand has a high probability of occurring in the confidence interval. Hierarchical scheduling strategy is developed to handle different intervals. In the first interval, which corresponds to the confidence interval, master problem under the predicted value is solved to acquire the resulting state of traditional generators day ahead, and subproblem for scenarios in confidence interval are added to improve the result. Interval optimization are used to simplify calculations of subproblem. Energy storage system is regulated in hourly unit commitment when real value is beyond the confidence interval to compensate the power imbalance of whole power system.

The simulation results of IEEE 30-bus power system reveal the effectiveness of the proposed UC model that considers both uncertain solar resource and load demand. Compared with the day-ahead UC, it is more flexible and adaptive to the volatility of net load demand. For real-time dispatch part, shorter computation time and lower operation cost show its advantages.

Note that the considered problem in this chapter is different from that in the preceding chapter. The day-ahead unit commitment in Chapter 2 considers the forecasted value. While the day-ahead unit commitment in Chapter 3 considers the confidence interval of forecasted value. Interval optimization [71] is used to ensure large possibility of net load demand value fall in the confidence level and obtain a more economical and safe operation scheduling. The end-points of the confidence interval are considered as the worst-case conditions which are formulated to simplify the interval optimization.

Chapter 4

Conclusion and Future Work

4.1 Conclusion

Unit commitment in power system is a nonlinear combinatorial optimization problem with typical large-scale mixed integers, which contains the discrete and continuous variables. Almost all of mathematical optimization methods for solving mixed integer programming are employed to deal with UC problem, but it is still difficult to find a perfect mathematical method which solves directly from the enormous amount of discrete variable space. UC not only reduces the operation cost for whole power system to achieve maximization of economic benefit, but also makes the operators in system run more smoothly. Therefore, many researchers are keen to find the optimal method in this field. This thesis firstly introduces related algorithms applied to UC problem, and the two main types of solution methods are reviewed. With the development of technology in renewable energy, including wind and solar power, the integration of renewable energy source in power system has received widespread attention in UC problem. The uncertainty and intermittence of renewable energy source become the urgent issues in UC problem to guarantee the stable operation of the power system.

Chapter 2 considers the uncertain solar resource, and designs a two-stage scheduling strategy to solve the problem on error of solar power output forecast to ensure the stable operation of the power system. ESS will be more flexible and make quick reactions in accordance with the power change in smart network. The proposed strategy to determine the state of ESS allows more efficient energy usage in power system.

Chapter 3 takes both volatile solar resource and load demand into account. Endpoints of confidence interval are considered to make the day-ahead schedule. Interval optimization method is utilized in the confidence interval to simplify computation complexity. Simulation results verify that the resulting state is more adaptive to the fluctuation of uncertain net load demand compared with an exiting algorithm. Energy storage system is committed hourly to deal with the larger error of day-ahead forecasted value to keep the whole power system balance. The computing time in hourly dispatch is acceptable under more economical operation and keeps a high utilization rate of energy storage system.

4.2 Future Work

For future work, we will investigate different probability distribution models of uncertain resource and load demand. 1) In this thesis, the normal distribution is considered as the model for the resource and load demand. In power industry, there are some resources that can be modelled as T distributions or beta distributions. Motivated by this observation, dealing with uncertain resource and load demand with more distribution models will be one of our future work. 2) In this thesis, the probability distribution models are assumed to be known. However, in practice, the uncertainties are usually difficult to be modeled. Recently, artificial intelligence and learning are being studied due to their wide applications in industries. In future, we will explore the possibility to apply learning based techniques (e.g., reinforcement learning) to deal with the uncertain resource and load demand.

In addition, we will study the UC problem on more practical systems, such as a large power network that involves generation areas which are interconnected by line.

Finally, more faults even outage which cause imbalance between supply and demand in power system will be studied to improve the quality and reliability of the power operation.

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Appendix A

Test Power System Data

A.1 IEEE 14-bus System [1]

A.1.1 Generator Data

Table A.1: IEEE 14-bus generators parameters

Unit	Bus No.	Pmax (MW)	Pmin (MW)	Min. ON(hr)	Min. OFF(hr)
1	1	150	50	1	1
2	2	50	20	1	1
3	3	80	12	1	1
4	6	45	10	1	1

A.1.2 Transmission Line Data

Table A.2: IEEE 14-bus transmission line data

Line No.	From Bus	To Bus	R(pu)	X(pu)	Full Line Charging Admittance(pu)	Flow Limits(MW)
1	1	2	0.0194	0.0592	0.0528	50

Line No.	From Bus	To Bus	R(pu)	X(pu)	Full Line Charging Admittance(pu)	Flow Limits(MW)
2	1	5	0.0540	0.2230	0.0492	65
3	2	3	0.0470	0.1980	0.0438	60
4	2	4	0.0581	0.1763	0.0374	60
5	2	5	0.0570	0.1739	0.0340	60
6	3	4	0.0670	0.1710	0.0346	60
7	4	5	0.0134	0.0421	0.0128	40
8	4	7	0.0000	0.2091	0.0000	65
9	4	9	0.0000	0.5562	0.0000	40
10	5	6	0.0000	0.2520	0.0000	65
11	6	11	0.0950	0.1989	0.0000	50
12	6	12	0.1229	0.2558	0.0000	50
13	6	13	0.0662	0.1303	0.0000	50
14	7	8	0.0000	0.1762	0.0000	50
15	7	9	0.0000	0.1100	0.0000	30
16	9	10	0.0318	0.0845	0.0000	50
17	9	14	0.1271	0.2704	0.0000	50
18	10	11	0.0821	0.1921	0.0000	50
19	12	13	0.2209	0.19999	0.0000	50
20	13	14	0.1709	0.3480	0.0000	50

A.1.3 Hourly Load Demand

Table A.3: IEEE 14-bus hourly load demand

Time(hr)	1	2	3	4	5	6	7	8
Load(MW)	181.30	170.94	150.22	103.60	129.50	155.40	181.30	202.03
Time(hr)	9	10	11	12	13	14	15	16
Load(MW)	212.38	227.92	230.51	217.56	207.20	196.84	227.92	233.10
Time(hr)	17	18	19	20	21	22	23	24
Load(MW)	220.15	230.51	243.46	253.82	259.00	233.10	225.33	212.38

A.1.4 Bus Load Factors

Table A.4: IEEE 14-bus load factors

Load	1	2	3	4	5	6
Bus	2	3	4	5	6	9
Load Factor	0.0838	0.3676	0.1846	0.0293	0.0432	0.1139
Load	7	8	9	10	11	
Bus	10	11	12	13	14	
Load Factor	0.0347	0.0135	0.0236	0.0521	0.0575	

A.1.5 Forecasted and Actual Solar Power Output

Table A.5: Hourly PV generation

Time(hr)	1	2	3	4	5	6	7	8
Forecasted(MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.0058	3.485
Actual(MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.0013	3.49
Time(hr)	9	10	11	12	13	14	15	16
Forecasted(MW)	8.655	12.233	16.523	18.698	22.475	26.385	23.575	18.574
Actual(MW)	10.654	12.354	14.689	17.563	20.916	25.265	21.234	15.152
Time(hr)	17	18	19	20	21	22	23	24
Forecasted(MW)	14.221	12.759	3.425	0.045	0.0	0.0	0.0	0.0
Actual(MW)	12.162	10.632	2.356	0.0245	0.0	0.0	0.0	0.0

A.2 IEEE 30bus System [2]

A.2.1 Generator Data

Table A.6: IEEE 30-bus generators parameters

Unit	Bus No.	Pmax (MW)	Pmin (MW)	Min. ON(hr)	Min. OFF(hr)
1	1	200	50	1	1
2	2	80	20	1	1
3	5	50	15	1	2
4	8	35	10	2	1
5	11	30	10	1	1

A.2.2 Transmission Line Data

Table A.7: IEEE 30-bus transmission line data

Line No.	From Bus	To Bus	R(pu)	X(pu)	Full Line Charging Admittance(pu)	Flow Limits(MW)
1	1	2	0.0192	0.0575	0.0528	300
2	1	3	0.0452	0.1852	0.0408	300
3	2	4	0.0570	0.1737	0.0368	300
4	3	4	0.0132	0.0379	0.00084	300
5	2	5	0.0472	0.1983	0.0418	300
6	2	6	0.0581	0.1763	0.0374	300
7	4	6	0.0119	0.0414	0.0090	300
8	5	7	0.0460	0.1160	0.0204	300
9	5	7	0.0267	0.0820	0.0170	300
10	6	8	0.0120	0.0420	0.0090	300
11	6	9	0.0000	0.2080	0	300
12	6	10	0.0000	0.5560	0	300
13	9	11	0.0000	0.2080	0	300

Line No.	From Bus	To Bus	R(pu)	X(pu)	Full Line Charging Admittance(pu)	Flow Limits(MW)
14	9	10	0.0000	0.1100	0	300
15	4	12	0.0000	0.2560	0	300
16	12	13	0.0000	0.1400	0	300
17	12	14	0.1231	0.2559	0	300
18	12	15	0.0662	0.1304	0	300
19	12	16	0.0945	0.1987	0	300
20	14	15	0.2210	0.1997	0	300
21	16	17	0.0824	0.1923	0	300
22	15	18	0.1073	0.2185	0	300
23	18	19	0.0639	0.1292	0	300
24	19	20	0.0340	0.0680	0	300
25	10	20	0.0936	0.2090	0	300
26	10	17	0.0324	0.0845	0	300
27	10	21	0.0348	0.0749	0	300
28	10	22	0.0727	0.1499	0	300
29	21	22	0.0116	0.0236	0	300
30	15	23	0.1000	0.2020	0	300
31	22	24	0.1150	0.1790	0	300
32	23	24	0.1320	0.2700	0	300
33	24	25	0.1885	0.3292	0	300
34	25	26	0.2544	0.3800	0	300
35	25	27	0.1093	0.2087	0	300
36	28	27	0.0000	0.3960	0	300
37	27	29	0.2198	0.4153	0	300
38	27	30	0.3202	0.6027	0	300
39	29	30	0.2399	0.4533	0	300
40	8	28	0.0636	0.2000	0.0428	300
41	6	28	0.0169	0.0599	0.0130	300

A.2.3 Hourly Load Demand

Table A.8: IEEE 30-bus hourly load demand

Time(hr)	1	2	3	4	5	6	7	8
Forecasted(MW)	148.0	132.0	125.0	100.0	86.0	110.0	130.0	156.0
Actual(MW)	145.0	130.0	122.0	100.0	90.0	108.0	120.0	150.0
Time(hr)	9	10	11	12	13	14	15	16
Forecasted(MW)	172.0	235.0	268.0	302.0	275.0	244.0	200.0	184.0
Actual(MW)	175.0	250.0	280.0	323.0	280.0	250.0	213.0	185.0
Time(hr)	17	18	19	20	21	22	23	24
Forecasted(MW)	150.0	127.0	116.0	179.0	213.0	175.0	154.0	142.0
Actual(MW)	142.0	125.0	105.0	166.0	220.0	180.0	153.0	140.0

A.2.4 Bus Load Factors

Table A.9: IEEE 30-bus load factors

Load	1	2	3	4	5	6	7
Bus	2	3	4	5	7	8	10
Load Factor	0.0765	0.0084	0.0268	0.3323	0.0804	0.1058	0.0204
Load	8	9	10	11	12	13	14
Bus	12	14	15	16	17	18	19
Load Factor	0.0395	0.0218	0.0289	0.0123	0.0317	0.0112	0.0335
Load	15	16	17	18	19	20	
Bus	20	21	23	26	29	30	
Load Factor	0.0077	0.0617	0.0122	0.0123	0.0084	0.0374	

A.2.5 Forecasted and Actual Solar Power Output

Table A.10: Hourly PV1 generation

Time(hr)	1	2	3	4	5	6	7	8
Forecasted(MW)	0.0	0.0	0.0	0.0	0.0	0.0	1.08	5.61
Actual(MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.86	5.55
Time(hr)	9	10	11	12	13	14	15	16
Forecasted(MW)	11.88	18.48	25.10	31.31	36.64	39.34	39.06	37.01
Actual(MW)	8.15	11.78	17.37	30.51	38.80	42.83	40.80	33.74
Time(hr)	17	18	19	20	21	22	23	24
Forecasted(MW)	32.92	27.17	20.48	13.68	7.54	2.03	0.00	0.00
Actual(MW)	32.86	27.79	36.24	12.44	6.42	2.09	0.00	0.00

Table A.11: Hourly PV2 generation

Time(hr)	1	2	3	4	5	6	7	8
Forecasted(MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.61	3.17
Actual(MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.54	3.14
Time(hr)	9	10	11	12	13	14	15	16
Forecasted(MW)	6.72	10.44	14.19	17.70	20.71	22.23	22.08	20.92
Actual(MW)	4.61	6.66	9.82	17.24	21.93	24.21	23.06	19.07
Time(hr)	17	18	19	20	21	22	23	24
Forecasted(MW)	18.60	15.36	11.57	7.73	4.26	1.14	0.00	0.00
Actual(MW)	14.45	12.82	9.29	3.62	2.62	1.18	0.00	0.00

Appendix B

Reference Case Model

B.1 Deterministic Hourly UC with ESS [3]

Objective Function:

$$min(\sum_{N_g} C_{g,t} + \sum_{N_e} C_{e,t})$$

Constraints:

$$\sum_{N_d} P_{d,t} = \sum_{N_g} p_{i,t} + \sum_{N_s} P^f_{s,t} + \sum_{N_e} P_{e,t}$$

$$PG_i^{min} * I_{i,t} \leq p_{i,t} \leq PG_i^{max} * I_{i,t}$$

$$p_{i,t} - p_{i,t-1} \leq RU_i I_{i,t-1} + SU_i(I_{i,t} - I_{i,t-1}) + PG_i^{max}(1 - I_{i,t})$$

$$p_{i,t-1} - p_{i,t} \leq RD_i I_{i,t} + SD_i(I_{i,t-1} - I_{i,t}) + PG_i^{max}(1 - I_{i,t-1})$$

$$-F_l \leq \sum_{N_b} T_{l,b} * (\sum_{N_g(b)} p_{i,t} + \sum_{N_s(b)} P^f_{s,t} + \sum_{N_e} P_{e,t} - \sum_{N_d(b)} P_{d,t}) \leq F_l$$

$$\sum_{T_i^{on}} [1 - I_{i,t}] = 0$$

$$\sum_{T_i^{off}} I_{i,t} = 0$$

$$\sum_{h=t}^{t+T_i^u-1} I_{i,h} \geq T_i^u(I_{i,t} - I_{i,t-1}), \forall t \in [T_{i0}^{on} + 1, N_t - T_i^u + 1]$$

$$\sum_{h=t}^{N_t} [I_{i,h} - (I_{i,t} - I_{i,t-1})] \geq 0, \forall t \in [N_t - T_i^u + 2, N_t]$$

$$\sum_{h=t}^{t+T_i^d-1} (1 - I_{i,h}) \geq T_i^d(I_{i,t-1} - I_{i,t}), \forall t \in [T_{i0}^{off} + 1, N_t - T_i^d + 1]$$

$$\sum_{h=t}^{N_t} [1 - I_{i,h} - (I_{i,t-1} - I_{i,t})] \geq 0, \forall t \in [N_t - T_i^d + 2, N_t]$$

$$E_{e,t} = E_{e,(t-1)} + \eta_e^C * P_{e,t}^C - \frac{1}{\eta_e^D} * P_{e,t}^D$$

$$E_e^{min} \leq E_{e,t} \leq E_e^{max}$$

$$P_e^{C,min} * u_{e,t}^C \leq P_{e,t}^C \leq P_e^{C,max} * u_{e,t}^C$$

$$P_e^{D,min} * u_{e,t}^D \leq P_{e,t}^D \leq P_e^{D,max} * u_{e,t}^D$$

$$u_{e,t}^C + u_{e,t}^D \leq 1$$

$$P_{e,t} = P_{e,t}^D$$

$$P_{e,t} = -P_{e,t}^C$$

B.2 Deterministic Day-ahead UC with ESS [4]

Objective Function:

$$min \sum_{N_t} (\sum_{N_g} C_{g,t} + \sum_{N_e} C_{e,t})$$

Constraints:

$$\sum_{N_d} P_{d,t} = \sum_{N_g} p_{i,t} + \sum_{N_s} P^f_{s,t} + \sum_{N_e} P_{e,t}$$

$$PG_i^{min} * I_{i,t} \leq p_{i,t} \leq PG_i^{max} * I_{i,t}$$

$$p_{i,t} - p_{i,t-1} \leq RU_i I_{i,t-1} + SU_i(I_{i,t} - I_{i,t-1}) + PG_i^{max}(1 - I_{i,t})$$

$$p_{i,t-1} - p_{i,t} \leq RD_i I_{i,t} + SD_i(I_{i,t-1} - I_{i,t}) + PG_i^{max}(1 - I_{i,t-1})$$

$$-F_l \leq \sum_{N_b} T_{l,b} * (\sum_{N_g(b)} p_{i,t} + \sum_{N_s(b)} P^f_{s,t} + \sum_{N_e} P_{e,t} - \sum_{N_d(b)} P_{d,t}) \leq F_l$$

$$\sum_{T_i^{on}} [1 - I_{i,t}] = 0$$

$$\sum_{T_i^{off}} I_{i,t} = 0$$

$$\sum_{h=t}^{t+T_i^u-1} I_{i,h} \geq T_i^u(I_{i,t} - I_{i,t-1}), \forall t \in [T_{i0}^{on} + 1, N_t - T_i^u + 1]$$

$$\sum_{h=t}^{N_t} [I_{i,h} - (I_{i,t} - I_{i,t-1})] \geq 0, \forall t \in [N_t - T_i^u + 2, N_t]$$

$$\sum_{h=t}^{t+T_i^d-1} (1 - I_{i,h}) \geq T_i^d(I_{i,t-1} - I_{i,t}), \forall t \in [T_{i0}^{off} + 1, N_t - T_i^d + 1]$$

$$\sum_{h=t}^{N_t} [1 - I_{i,h} - (I_{i,t-1} - I_{i,t})] \geq 0, \forall t \in [N_t - T_i^d + 2, N_t]$$

$$E_{e,t} = E_{e,(t-1)} + \eta_e^C * P_{e,t}^C - \frac{1}{\eta_e^D} * P_{e,t}^D$$

$$E_e^{min} \leq E_{e,t} \leq E_e^{max}$$

$$P_e^{C,min} * u_{e,t}^C \leq P_{e,t}^C \leq P_e^{C,max} * u_{e,t}^C$$

$$P_e^{D,min} * u_{e,t}^D \leq P_{e,t}^D \leq P_e^{D,max} * u_{e,t}^D$$

$$u_{e,t}^{C} + u_{e,t}^{D} \leq 1$$

$$P_{e,t} = P_{e,t}^{D}$$

$$P_{e,t} = -P_{e,t}^{C}$$