Engineering Applications of Computational Methods 14

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Artificial Intelligence Enabled Computational Methods for Smart Grid Forecast and Dispatch

Springer

Engineering Applications of Computational Methods

Volume 14

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ISSN 2662-3366 ISSN 2662-3374 (electronic)
Engineering Applications of Computational Methods
ISBN 978-981-99-0798-4 ISBN 978-981-99-0799-1 (eBook)
https://doi.org/10.1007/978-981-99-0799-1

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Foreword

With the increasing penetration of renewable energy and flexible loads in smart grids, a more complicated power system with high uncertainty is gradually formed, which accordingly brings great challenges to smart grid forecast and dispatch. Traditional methods usually require knowing accurate mathematical models, and they cannot well deal with the growing complexity and uncertainty. Fortunately, the widespread popularity of advanced meters makes it possible for smart grids to collect massive data, which offers opportunities for data-driven artificial intelligence (AI) methods to address the forecast and dispatch issues. In fact, big data and AI-enabled computational methods are widely deployed nowadays. People from different industries try to apply AI-enabled techniques to solve practical yet challenging problems. The power and energy industry is no exception. AI-enabled computational methods can be utilized to fully explore the value behind these historical data and enhance electric services such as power forecast and dispatch.

This book explores and discusses the applications of AI-enabled forecast and dispatch techniques in smart grids. The contents are divided into three parts. The first part (Chaps. 1–3) provides a comprehensive review of recent developments in smart grid forecast and dispatch, respectively. Then, the second part (Chaps. 4–7) investigates the AI-enabled forecast approaches for smart grid applications, such as load forecast, electricity price forecast and charging power forecast of electric vehicle charging station. On this basis, the smart grid dispatch issues are introduced in the third part (Chaps. 8–11). This part introduces the application of extreme learning machine, data-driven Bayesian assisted optimization algorithm, multi-objective optimization approach, deep reinforcement learning as well as the federated learning, etc. Finally, the future research directions of smart grid forecast and dispatch (Chap. 12) are presented. This book presents model formulations, novel algorithms, in-depth discussions and comprehensive case studies.

One author of this book, Prof. Zhigang Zeng, is an internationally established researcher in the area of AI. He has also conducted extensive work in the application of AI in smart grids. Moreover, another author Prof. Lei Wu is an expert in the smart grid dispatch and serves as associate editors of several top-tier international journals. Prof. Yong Zhao, one of the coauthors, has engaged in several practical projects and accumulated valuable experience in smart grid research. The first author, Prof. Yuanzheng Li, has conducted research in smart grid for a long time with more than 15 years, published a variety of academic papers and finished many practical projects. It is a worthy reading book, and potential readers will benefit much from AI perspective and how AI-enabled computational methods are used in smart grid forecast and dispatch.

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Preface

As the next generation of power system, smart grid is devoted to achieving a sustainable, secure, reliable and flexible energy delivery through decolonization, decentralization and digitization. In order to realize the modernization of power system, increasing penetration of renewable energy is integrated into the smart grid, which also challenges the reliability, stability and flexibility of the power and energy system. Furthermore, a large number of distributed energy resources such as photovoltaic, wind power and electric vehicles make the smart grid more decentralized and complicated. Meanwhile, data acquisition devices such as advanced meters are gaining popularity, which enables an immense amount of fine-grained electricity data to be collected. To this end, the modern smart grid calls for making the best utilization of these history data and promoting the power system operation.

Under this background, data-driven artificial intelligence computation approaches are applied in the power and energy system to address the forecast and dispatch issues. In fact, AI-enabled computational methods and machine learning techniques such as deep learning, reinforcement learning and federated learning have been greatly and considerably developed in recent years. It seems natural to figure out how to apply these state-of-the-art techniques to uncertainty forecast and energy dispatch. However, it is a predicament in the power industry that even though an increasing and huge number of smart meter data are collected, these data are not yet fully utilized due to the complexity, uncertainty as well as the privacy concern of power system. As a result, our book aims to take full advantage of numerous data and advanced AI techniques to present some successful applications and also inspire more valuable thoughts, which is quite important for both academia and industry.

This book is a monograph about the AI-enabled computational methods for smart grid forecast and dispatch, which consists of 12 chapters. It begins with an overview of the basic concepts of smart grid forecast and dispatch in terms of problem statement and property. Since uncertainty forecast is the basis of further smart grid dispatch and its applications, three issues on AI-enabled forecast approaches, i.e., electrical load forecast, electricity price forecast and electrical vehicle charging station charging power forecast are subsequently studied. On this basis, the following works try to depict the increasing dynamic and complicated smart grid dispatch issues. Specific works include reinforcement learning, federated learning, machine learning as well as the AI assisted evolutionary algorithm are introduced in this book. Finally, prospects of future research issues on smart grid forecast and dispatch are provided at the end of this book.

To help readers have a better understanding of what we have done, we would like to make a simple review of the 12 chapters in the following.

Chapter 1 conducts a brief introduction of smart grid forecast and dispatch issues, including the concept of smart grid and application-oriented review of forecast and dispatch techniques. Following the three stages of analytic, namely descriptive, predictive and prescriptive analytic, the key problem statement and property are identified at this chapter.

Chapter 2 provides a comprehensive review of smart grid forecast and decomposes the key application areas into three aspects from the perspective of consumers: the load and netload forecast, the electricity price forecast as well as the electrical vehicle charging station charging power forecast. On this basis, the research framework for smart grid forecast is established in this chapter.

Chapter 3 offers a application-oriented survey of dispatch techniques and methodologies in the smart grid. Some real-world applications regarding smart grid dispatch are introduced in this chapter, including distribution network, microgrid network, electric vehicle and the integrated energy system. After that, the classical methods for smart grid dispatch are divided into three categories, i.e., mathematical programming, evolutionary algorithm and AI-enabled approached, which are discussed in detail, respectively.

Chapter 4 develops a novel deep learning model for deterministic and probabilistic load forecasting. In this model, unshared convolution neural network is selected as the backbone, which is the first time of applying unshared convolution to load fore casting. By reconstructing the unshared convolution layers into the densely connected structure, this architecture has a good nonlinear approximation capability and can be trained in the end-to-end fashion.

Chapter 5 proposes a reinforcement learning assisted deep learning probabilistic forecast framework for the charging power of EVCS. This framework contains a data transformer method to preprocess the charging session data and a probabilistic forecast algorithm, termed as LSTM-AePPO. In this framework, the LSTM is used to forecast the mean value of the forecast distribution, and the variation of its cell state is modeled as an MDP. Then, a reinforcement learning algorithm, AePPO, is applied to solve the MDP model and calculate the variance of the forecast distribution.

Chapter 6 presents an effective DL based DAEPF model for deterministic and interval forecasting. In recognizing that the temporal variability exists in electricity price datasets, the coherently aggregating structure of unshared convolution neural network and gated recurrent unit is proposed to extract multi-term dependency features. Considering the feature-wise variability, the feature-wise attention block is proposed for autoweighting in the feature dimension.

Chapter 7 introduces a Dirichlet mixture model based on data association and improve the posterior distribution by variational inference method, so that the posterior distribution takes more information on net load data association into account. Thus, the lower bound of the improved evidence is constructed so that the DDPMM obtains a suitable variational distribution through this lower bound, and its convergence is proved by combining it with the EM algorithm.

Chapter 8 proposes a multi-objective ED (MuOED) model with uncertain wind power. In this model, the expected generation cost, the upside potential and the downside risk are taken into account at the same time. Then the MuOED model is formulated as a tri-objective optimization problem, and we use an extreme learning machine assisted group search optimizers with multiple producers to solve the problem. Afterward, a fuzzy decision-making method is used for choosing the final dispatch solution.

Chapter 9 depicts a coordinated stochastic scheduling model of electric vehicle and wind power integrated smart grid to conduct the comprehensive investigation among wind power curtailment, generator cost and pollution emission. Specially, the proposed model considers uncertainties of wind power and calculates wind power curtailment by probabilistic information. Besides, we propose the parameters adaptive differential evolutionary algorithm to solve the above optimal issue in an efficient way.

Chapter 10 presents a many-objective distribution network reconfiguration model with stochastic photovoltaic power. In this model, the objective function involves the photovoltaic power curtailment, voltage deviation, power loss, statistic voltage stability, and, generation cost. Then, a deep reinforcement learning assisted multi-objective bacterial foraging optimization algorithm is proposed to solve the above many-objective distribution network reconfiguration model.

Chapter 11 designs a federated multi-agent deep reinforcement learning algorithm for the multi-microgrids system energy management. A decentralized multi-microgrids model is built first, which includes numerous isolated microgrids and an agent is used to control the dispatchable elements of each microgrid for its energy self-sufficiency. Then, the federated learning mechanism is introduced to build a global agent that aggregated the parameters of all local agents on the server and replaces the local microgrid agent with the global one.

Chapter 12 discusses some research trends in the smart grid forecast and dispatch, such as big data issues, novel machine learning technologies, new distributed models, the transition of smart grids and data privacy and security concern. On this basis, a relatively comprehensive understanding about the challenges of current forecast and dispatch approaches, potential solutions and future directions are depicted in this chapter.

In conclusion, this book provides various applications of the state-of-the-art AI-enabled forecast and dispatch techniques for the smart grid operation. We hope this book can inspire readers to define new problems, apply novel methods and obtain interesting results with massive history data in the power systems.

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Acknowledgments

This book made a summary of our research about smart grid forecast and dispatch achieved in recent years. These works were carried out in the School of Artificial Intelligence and Automation, Ministry of Education Key Laboratory of Image Processing and Intelligence Control, Huazhong University of Science and Technology, Wuhan, China.

Many people contributed to this book in various ways. The authors are indebted to Mr. Zhixian Ni, Mr. Jingjing Huang, Mr. Chaofan Yu, Mr. Shangyang He, Mr. Guokai Hao, Mr. Tianle Sun, Mr. Yizhou Ding, Mr. Fushen Zhang and Mr. Jun Zhang from Huazhong University of Science and Technology, who have contributed materials to this book and thank for their assistance in pointing out typos and checking the whole book.

In addition, we appreciate the staff at Springer for their assistance and help in the preparation of this book.

This work is supported in part by the National Natural Science Foundation of China (Grant 62073148), in part by Key Project of National Natural Science Foundation of China (Grant 62233006) and in part by Key Scientific and Technological Research Project of State Grid Corporation of China (Grant No. 1400-202099523A-0-0-00). The authors really appreciate their supports.

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Contents

Chapter 1
Introduction for Smart Grid Forecast and Dispatch

As a novel generation of power systems, smart grid is devoted to achieving a sustainable, secure, reliable and flexible energy delivery through the bidirectional power and information flow. In general, the smart grid mainly possesses the following features.

(1) Smart grid offers a more efficient way to ensure the optimal dispatch with a lower generation cost and higher power quality via the integration of distributed sources and flexible loads, such as renewable energy and electric vehicles [1–5].
(2) Smart grid achieves the secure and stable operation of power system via the deployment of effective operational control technologies, including the automatic generation control, autonomous voltage control and load frequency control [6–9].
(3) Smart grid provides a transaction platform for customers and suppliers affiliated to different entities, thus enhances the interactions between suppliers and customers, which facilitates the development of electricity market [10–12].
(4) Smart grid equips numerous advanced infrastructures including sensors, meters and controllers, which also arises some emerging issues, such as the network security and privacy concern [13–16].

On this basis, the typical architecture of smart grid is depicted in Fig. 1.1, which illustrates that the operation of smart grid involves four fundamental segments, i.e., power generation, transmission, distribution and customers. As for the generation part, traditional thermal energy is converted to electrical power, and the large-scale of renewable energy integration is a trend in smart grid. After that, the electrical energy is delivered from the power plant to the power substations via the high-voltage transmission lines. Then, substations lower the transmission voltage and distribute the energy to individual customers such as residential, commercial and industrial loads. During the transmission and distribution stages, numerous smart meters are deployed in the smart grid to ensure the secure and stable operation. Besides, the

Y. Li et al., *Artificial Intelligence Enabled Computational Methods for Smart Grid Forecast and Dispatch*, Engineering Applications of Computational Methods 14,
https://doi.org/10.1007/978-981-99-0799-1_1

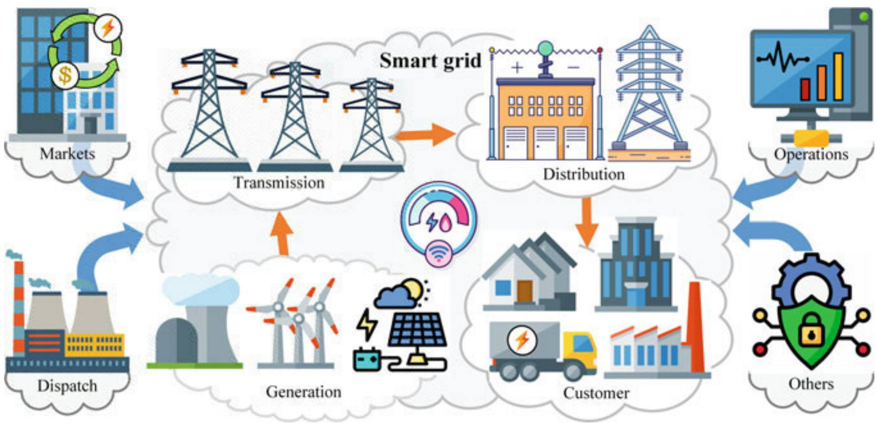

Fig. 1.1 Typical architecture of smart grid

prevalent of these advanced infrastructures also brings about some emerging issues that traditional power system seldom encounter, e.g., the network security and privacy concern.

Among the various smart grid operation issues, forecast and dispatch are regarded as the most critical segments. One the one hand, smart grid forecast offers a precious information for the uncertain future status, which significantly assists the smart grid to prevent and defuse the potential risks . On the other hand, smart grid dispatch contributes to optimal operation of power system, which promotes the efficiency of energy utilization as well as the stability of the whole system. In this way, extensive previous research has devoted to investigate these two directions, which has already achieved quite successful applications. In the rest part of this section, comprehensive introduction regarding the smart grid forecast and dispatch is presented as follows.

1.1 Smart Grid Forecast

Forecasting techniques are essential to the operation of the smart grid, and it is capable to provide crucial references, such as load and electrical price for the schedule and planning of the power system [17–19]. The precious of forecasting highly influence the decision performance of the smart grid [17]. Generally, the forecasting techniques can be represented as follows:

$$Y = F_\theta(X) \tag{1.1}$$

where Y is the forecast value, normally stands for the load, electricity price and demands; F_θ denotes the forecast model with parameter θ and X is the inputs. The θ is usually determined by the experiences of algorithm designer or through the historical data. Besides, the forecasting would apply autoregression, that is, $Y = X_t$

and $X = X_{[t-1,t-2,...,t-T]}$ where T indicates the order of the regression model [20, 21]. It should be noted that the forecasting can be categorized in to three types on the basis of the time interval [22].

- The long-term technique focuses on the forecasts about 1 year to 10 years ahead. The values are mainly used for the long-term planning of the smart grid, including the future direction and the assessment of a smart grid [23, 24].
- The medium-term forecasting technique mainly takes the consideration of the predict value about 1 mouth to 1 year ahead. The economic efficiency, security guarantee and maintenance of the power system are the chief topics during this time interval [25].
- The recent industry and academia both concentrate on the forecasting on less time interval, namely about 1 hour to 1 day ahead, and this is describe as the short-term forecasting. It is due to the optimal economic dispatch in smart grid, the optimum unit commitment and the evaluation of contracts between various companies would rely on the precious forecasting value to achieve an efficient performance [24, 26].

Traditionally, the above forecast in the smart grid can be done through statistical methods such as Box–Jenkins basic models, Kalman filtering (KF)[27], gray method (GM)[28] and exponential smoothing (ES)[29]. The Box–Jenkins basic models include autoregressive (AR)[30], moving average (MA)[31] autoregressive moving average (ARMA)[32] and autoregressive integrated moving average (ARIMA) models[33]. In AR, the forecast value can be expressed as a linear combination of previous data. The MA method mimics the moving average process; it is a linear regression model that forecasts future values through the white noise of one or more past values. ARMA model combines both AR and MA, and the ARIMA further enhances the ability of the algorithm on the non-stationary data[34]. Besides, the KF method is efficient, especially in long-term forecasting, and is capable of dealing with errors with multi-inputs. Therefore, the numerous elements that may influence the forecast performance should be considered, such as weather, time, economy, random disturbances, and other customer factors. Moreover, GM is widely applied in the scenario with limited past data and the ES can be carried from the exponentially weighted average of the past observation.

With the development of machine learning techniques, support vector machines (SVMs)[28], the artificial neural network (ANN)[35], extreme learning machines (ELM)[36] and wavelet neural networks (WNNs)[37] are emerging for the forecast problem in the smart grid. The SVM model could deploy a hyperplane that separates the data that is mapped into a higher feature dimensional space through a nonlinear mapping function. In this way, the algorithm is capable to model the nonlinear relationship between the input and the forecast value. The ANN has gained huge popularity in recent decades because of the development of big data and advanced computation hardware [38]. Basically, it is capable of fitting the nonlinear relationship when conducting forecasting, the burgeoning recurrent neural network (RNN) and Transformer-family model further endow the time and space dependency for the forecasting, which further improves the forecasting accuracy of the model [29, 39]. The ELM is a special case of a feedforward neural network that only contains a single-hidden layer. By analytically solving the corresponding least-squares problem, the weights of the ELM can be simply determined. WNN takes the advantage of the wavelet function and thus can recognize a feature extraction without too much prior information. This means the algorithm is robust for approximating the nonlinear function [40].

Despite the above significant progress in the field of smart grid forecasting, the related fields are still developing. Nowadays, its main research focuses on the following aspects:

1. **Increasing the accuracy of the forecasting techniques**
   Although current methods have achieved sufficient performance, the forecasting accuracy is still inadequate due to numerous reasons. First, the forecasting method would be underfitting due to the inappropriate model or training method. Besides, the performance of the methods would decrease when forecasting the peak or some emergencies happened. Overall, the forecasting values are fully trusted only if their accuracy raise to a higher level.
2. **Tackle the distribution training and application of the forecasting method**
   With the development of renewable energy techniques and the electrical market, more and more distributed microgrids are being developed. Since microgrids have become the main subject of the smart grid, their distribution characteristic requires distributed forecasting techniques. Different from the traditional grids with central operators, the distributed microgrids have their own management center for power dispatch and energy transactions. In this way, forecasting techniques, especially ML methods, should develop new approaches for this change.
3. **Raising the explainability of ML techniques**
   The black box feature of the current ML techniques limits its wide application in the industry. On the one hand, the experiences of human experts cannot accelerate the training of ML methods. On the other hand, the knowledge of ML methods that are trained through numerous data is impossible to be learned by humans, which reduced the credibility of the methods. Therefore, the exploration of the explainability of ML is necessary, which could develop more transparent ML methods and thus become more inspired for wider applications.

1.2 Smart Grid Dispatch

1.2.1 Problem Statement

Power dispatch is a pivotal problem that must be addressed in achieving the smart grid promise [41]. In order to decide the optimal strategy for power generation, transmission and even consumption, smart grid dispatch connects different components within the whole power system. To be specific, the purpose of power dispatch aims at reasonably arranging the generation schemes to each generator and determining the operation states of transformers and other power equipment, so as to optimize some performance indicators while satisfying the constraint conditions at the same time. Generally, the smart grid dispatch could be converted into an optimization problem, which is expressed as follows.

$$\begin{aligned}&\min f(x)\\ &\text{s.t.}\ \begin{cases} g(x) = 0, \\ h(x) \le 0, \end{cases}\end{aligned} \tag{1.2}$$

where x denotes the decision variables of smart grid (e.g., outputs of generators,) and $f(x)$ represents the objective function (e.g., the fuel cost, the voltage deviation, transmission loss and etc.). Besides, $g(x)$ and $h(x)$ are equality constraints (e.g., power balance constraints) and inequality constraints (e.g., output limits of equipment), respectively. In fact, smart grid dispatch problems will have different formulations under different requirements or assumptions. Therefore, some popular formulations of smart grid dispatch are summarized in this section.

(a) Economic Dispatch (ED)

ED is one of the fundamental problems in the smart grid, which allocates generation among different generation units to achieve the minimum operation cost without considering the transmission network constraints [42]. In general, ED is the simplest formulation of smart grid dispatch that is usually utilized for real-time operation as follows.

$$\begin{aligned}&\min c\left(P_{\mathrm{G}}\right)\\ &\text{s.t.}\ \begin{cases} \sum_G P_{\mathrm{G}} - \sum_D P_{\mathrm{D}} = 0 \\ P_{\mathrm{G}}^{\min} \le P_{\mathrm{G}} \le P_{\mathrm{G}}^{\max} \end{cases}\end{aligned} \tag{1.3}$$

where G represents the set of power generators and D is the set of load demands. P_G and P_D denote the outputs of generator and load demands, respectively. Hence, $c(P_G)$ is the total cost function, which could be calculated by linear function (i.e., $c(P_G) = \sum(\alpha + \beta P_G)$) or nonlinear quadratic function $c(P_G) = \sum(\alpha + \beta P_G + \gamma P_G^2)$. In addition, the power balance constraint is presented by the first constraint, without considering the power flow through transmission lines and the second constraint depicts the limits of generator outputs.

(b) Optimal Power Flow (OPF)

Despite ED achieves quite successful applications in power system, it only finds the optimal dispatch for generators, which are constrained within their output limits and results in a balance between total generation and load demands. However, the ED calculation ignores the effect that the dispatch of generation has on the loading of transmission lines or the effect it has on bus voltages. In fact, the dispatch solution of generators does have a significant affects on power flows, which should be taken into account under some circumstances. To this end, the optimal power flow is proposed as an extension of classic ED model, which couples the power flow calculation with the ED calculation so that the power flow and ED are optimized, simultaneously [43]. The original formulation of OPF is expressed as follows:

$$\min \sum_{Gi \in G} c\left(P_{\mathrm{G}i}\right)$$
$$\text{s.t.} \begin{cases} P_{Gi} - P_{Di} - \sum_{j \in i} V_i V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right) = 0 \\ Q_{Gi} - Q_{Di} - \sum_{j \in i} V_i V_j \left(G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij}\right) = 0 \\ P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \\ Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \\ V_i^{\min} \le V_i \le V_i^{\max} \\ |S_{\mathrm{ij}}| \le S_{\mathrm{ij}}^{\max} \end{cases} \tag{1.4}$$

where P_{Gi} and Q_{Gi} are the active and reactive power of generator i. P_{Di} and Q_{Di} denote the active and reactive power demand of bus i. V_i represents the voltage magnitude of bus i and θ_{ij} denotes the difference of voltage phase between bus i and j. G_{ij} and B_{ij} are the real and imaginary part of the mutual admittance, respectively. Besides, S_{ij} is the power flow, and $S_{\mathrm{ij}}^{\max}$ represents the transmission capacity of the branch connecting bus i and j. The power flow equations are addressed by the first two constraints, while the next four constraints depict the limitation of generator, bus and branch, respectively.

(c) Energy Management

With the increasing penetration of highly fluctuated renewable energy, power system is confronted with rigorous challenge, which is mainly due to the imbalance between power supply and demand. Actually, the shortage/excess in the consumption or generation of power may perturb the smart grid and create serious problems such as voltage deviation and even blackouts in severe conditions. Therefore, energy management is applied to increase the balance between supply and demand in an efficient way, and to reduce the peak load during unexpected periods. Generally, energy management can be divided into two main categories. On the one hand, the first one is from the perspective of electricity supply, which uses the energy management to define the adequate scheme of generation units in an efficient way, which is also named unit commitment. A classical formulation of energy management is presented as follows:

$$\min \sum_t \left(c_1\left(P_{\mathrm{G},t}\right) + c_2\left(u_{\mathrm{G},t}\right) + c_3\left(\mathrm{su}_{\mathrm{G},t}\right) + c_4\left(\mathrm{sd}_{\mathrm{G},t}\right)\right)$$
$$\text{s.t.} \begin{cases} \sum_G P_{\mathrm{G},t} - \sum_D P_{\mathrm{D},t} = 0 \\ u_{\mathrm{G},t} P_{\mathrm{G}}^{\min} \le P_{\mathrm{G},t} \le u_{\mathrm{G},t} P_{\mathrm{G}}^{\max} \\ u_{\mathrm{G},t} = u_{\mathrm{G},t-1} + \mathrm{su}_{\mathrm{G},t} - \mathrm{sd}_{\mathrm{G},t} \\ \sum_t \mathrm{su}_{\mathrm{G},t} \ge \mathrm{SU}_{\mathrm{G}} \\ \sum_t \mathrm{sd}_{\mathrm{G},t} \ge \mathrm{SD}_{\mathrm{G}} \end{cases} \tag{1.5}$$

where $c_1(\cdot)$, $c_2(\cdot)$, $c_3(\cdot)$ and $c_4(\cdot)$ represent the fixed cost, variable cost, startup cost and shutdown cost of generation units, respectively. $u_{G,t}$, $\mathrm{su}_{\mathrm{G,t}}$ and $\mathrm{sd}_{\mathrm{G,t}}$ denote the decisions of unit commitment, startup and shutdown. As mentioned before, the power balance constraint is addressed by the first constraint, while the second constraint presents the limitation of generator outputs. Besides, the status of generation units is denoted by the third constraint, while the last two address the minimal startup and shutdown time constraints.

On the other hand, the second category is on the consumer side, in which consumers manage their energy consumption in order to meet the available power from the generation side, which is also called demand response. More specific, the consumer side energy management provides an opportunity of users to play an important role int he operation of smart grid by shifting or reducing their energy usage during peak periods in response to time-based rates or other forms of financial incentives.

(d) Network Reconfiguration

Network reconfiguration could be defined as altering the network topological structures by changing the open/close status of tie switches while satisfying operation constraints [44]. This process can improve the performance of smart grid according to different particular objectives and constraints. The formulation of original network reconfiguration is presented as follows:

$$\min P_{\text{loss}} + \Delta V_D$$
$$\text{s.t.} \begin{cases} P_{Gi} - P_{Di} - \sum_{j\in i} V_i V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 \\ Q_{Gi} - Q_{Di} - \sum_{j\in i} V_i V_j \left(G_{ij}\cos\theta_{ij} - B_{ij}\sin\theta_{ij}\right) = 0 \\ V_i^{\min} \le V_i \le V_i^{\max} \\ 0 \le I_i \le I_i^{\max} \\ \text{Radial topological constraints} \end{cases} \tag{1.6}$$

where the fourth constraint addresses the limitation of line current and the radial network structure must be maintained and all loads should be served after reconfiguration, as the last constraint denoted.

1.2.2 Problem Properties

The objective functions and operation constraints of smart grid dispatch determine that this problem has the following characteristics [45]:

(a) Multi-objective

It should be noted that the optimization objectives of smart grid dispatch are diverse from different perspectives. For instance, the owner of renewable power plant prefers to promote the utilization of renewable energy, in order to gain more revenue. However, the large-scale integration of renewable energy may threaten the secure operation of power system, which is confronted with the optimization objective of smart grid. Therefore, smart grid dispatch cannot consider only one optimization objective. Actually, the dispatcher usually needs to consider several objectives in the real smart grid, such as the generation cost, voltage deviation and power loss, which is a multi-objective optimal dispatch problem of power system.

(b) Multi-constraint

Due to the particularity of power system, the smart grid dispatch problem is a multi-constraint one. At first, the power generation and load demand must be balanced in real-time since the electricity cannot be stored in a large scale. Afterward, considering the effect of generation dispatch on transmission lines, the classic energy conservation should be extended to power flow constraints, which determine the power distribution of smart grid. In addition, the outputs of electrical appliance should also be constrained as a result of their physical limitation. At last, the secure constraints of smart grid need to be satisfied including the apparent power on transmission lines, the voltage amplitude of power buses and etc. Consequently, the smart grid dispatch problem is formulated as an optimization model with multiple constraints.

(c) Multi-variable

In order to achieve the economic and secure operation of smart grid, numerous decision variables should be dispatched including the power outputs of generator, the terminal voltage amplitude of generator, the tap position of transformer and controllable status of electrical equipment. Therefore, the smart grid dispatch problem in reality is accompanied with high-dimensional decision variables due to the extensive scale of power system. For example, the dimension of decision variables in IEEE 118-bus power system is up to 238, while the total number of decision variables in China Southern Power Grid is more than ten thousand. Worse of all, some variable of smart grid dispatch are continuous, while some other are discrete, which leads to this problem hard to be solved.

(d) Strong uncertainty

With large-scale renewable energy integrated into the power system, its strong uncertainty brings about serious challenges to the dispatch of smart grid. First of all, the outputs of renewable energy are intermittent such as solar power and hydroelectricity, which makes the peak load regulation difficult. Secondly, the randomness of renewable energy may threaten the secure and stable operation of smart grid, e.g., voltage deviation, power loss or even congestion. Finally, the generation of renewable energy is uncontrollable to some extent, which aggravates the dispatch burden of smart grid. In addition, the consumption behavior of load users is also random, which leads to the uncertainty of demand side.

(e) Computational complexity

Taking aforementioned four aspects into account, we could make a conclusion that the smart grid dispatch is a complicated optimization problem with multi-objective, multi-constraint, multi-variable and strong uncertainty. This is the reason why smart grid dispatch problem has attracted much attention in recent years. In order to handle this complex problem and meet the requirement of practical application, several methods are proposed, which will be introduced in Chap. 3 with detailed explanation.

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