IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received July 23, 2019, accepted August 6, 2019, date of publication August 9, 2019, date of current version August 26, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2934164

Research on Medium- and Long-Term Operation Simulation Method Based on Improved Universal Generating Function

ZHEYU GUO[1], YANAN ZHENG[1,2], (Member, IEEE), AND GENGYIN LI[1], (Member, IEEE)
[1]School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102206, China
[2]Energy Research Institute, Chinese Academy of Macroeconomic Research, Beijing 100038, China
Corresponding author: Yanan Zheng (zhengyn@eri.org.cn)

ABSTRACT The development of technologies in generation-grid-load-energy storage has created enormous uncertainties for power system and thus brings great challenges to medium-and long-term operation simulation. In order to describe uncertainties in medium-and long-term operation process and analyze operation condition objectively, this paper firstly builds multi-state probabilistic models of generation-grid-load-energy storage based on multi-state analysis method, and adopt Markov method to consider state dependency of some components. And then using these models, an operation simulation method based on the improved universal generating function is proposed in which the minimum distance classification method is adopted to improve computational efficiency and avoid state explosion problem. At last the validation and engineering practicality of the proposed method are demonstrated in IEEE RTS-79 and Zhangjiakou power system respectively, and the suitable areas of different operation simulation method are also discussed.

INDEX TERMS Medium-and long-term operation simulation, multi-state analysis, universal generating function, uncertainty analysis.

NOMENCLATURE

ABBREVIATIONS

DR	demand response
EENS	expected energy not supply
IDR	incentive-based demand response
LOLE	lose of load expectation
LOLP	loss of load probability
PDR	price-based demand response
PPS	probabilistic production simulation
PV	photovoltaic
RE	renewable energy
UCED	unit commitment and/or economic dispatch
UGF	universal generating function
VPP	virtual power plant

PARAMETERS

α, β	shape parameters of Beta distribution
c	scale parameter of Weibull distribution
C	LOLP limit of a system
$Cost\ (i)$	operation cost of unit (or equivalent unit) i
η_{ch}, η_{dis}	charging and discharging efficiency of an energy storage facility
$G_{\mathrm{t}}^{ch}, G_{\mathrm{t}}^{dis}$	average charging and discharging power of energy storage facility in period t
$I_i(t)$	light intensity that PV unit i received in period t
$I_{\max}$	maximum light intensity in an area
$ind(t)$	day-night index (equal to 1 if in the daytime and 0 if at night)
k	shape parameter of Weibull distribution
$L(t)$	load in period t
$L_0(t)$	load before implementing price-based demand response in period t
$\bar{L}_{peak}, \bar{L}_{flat}$	average load in peak period and in flat period respectively
λ_D, μ_D	peaking unit's fault rate and repair rate under derating state
$\lambda_{p-v}, \lambda_{f-v}, \lambda_{p-f}$	peak-valley, flat-valley and peak-flat load transfer rate
λ_T, μ_T	peaking unit's fault rate and repair rate under rating state

The associate editor coordinating the review of this article and approving it for publication was Xiaorong Xie.

$M(t)$	state transition matrix of peaking unit in period t
$n_{(m)}(t)$	state number of system containing m units in period t
$P_{de,i}$	output of unit i under derating state
P_{Ni}	rating power of unit i
$p_{ro,i}^{FOR}$	forced outrage rate of unit i
$p_{ro,i}^{P}(t)$, $p_{ro,i}^{D}(t)$, $p_{ro,i}^{F1}(t)$, $p_{ro,i}^{F2}(t)$, $p_{ro,i}^{R2}(t)$	probabilities of unit i under planned outage, derating, forced outage 1, forced outage 2, rating, ramp state 1 and ramp state 2 respectively
P_s	rating power of energy storage facility
ρ_{1+}, ρ_{1-}	need rate and needless rate from planned outage to derating state of a peaking unit
ρ_{2+}, ρ_{2-}	need rate and needless rate from derating state to rating state of a peaking unit
$S_{SOC\max}$, $S_{SOC\min}$	maximum storage capacity and minimum storage capacity
T	research cycle
T_{peak}, T_{flat}, T_{valley}	time set of peak, flat and valley period respectively
T_{R1}, T_{R2}	ramp time of a peaking unit from planned outage to derating state and from derating state to rating state respectively
θ	confidence probability for maximum power supply capacity
v	wind speed at wind turbine impeller hub
v_{Ni}, $v_{in,i}$, $v_{out,i}$	wind turbine's rating wind speed, cut-in wind speed and cut-off wind speed

VARIABLES

$C_{\max}^{\theta}(t)$	maximum power supply capacity with confidence probability of θ
$EENS\ (m,t)$	EENS of system m in period t
$G_{t,aver}^{ch}$, $G_{t,aver}^{dis}$	expectations of system output greater than load and less than load respectively
$LOLP\ (m,t)$	LOLP of system m in period t
$P_i^k(t)$, $p_{ro,i}^k(t)$	output of the kth state of unit i and corresponding probability
$P_{(m)}^k(t)$, $p_{ro,(m)}^k(t)$	output and corresponding probability of subsystem m's kth state in period t
$S_{SOC}(t)$	stored electricity of an energy storage facility in period t
x_i^k, $p_{ro,i}^k$	the kth state and corresponding probability of element i in universal generating function

FUNCTIONS

$\Gamma(\cdot)$	gamma function

I. INTRODUCTION

Generation expansion planning is one of the most discussed topics in the power system fields, and operation simulation is an important part of it [1], [2]. However, with the development of technologies such as renewable energies (RE), demand response (DR) and energy storage, the uncertainties of power generation, power grid, power load and energy storage (generation-grid-load-energy storage) grow with each passing day, which brings great challenges to power system operation simulation. Moreover, comparing with short-term, medium-and long-term will show more uncertainties and the difficulty of medium-and long-term operation simulation is further increased [3]–[5], where short-term refers to the 1 to 2 years recently, and the medium- and long-term usually refers to 3 years or more in the future. Therefore, aiming at medium-and long-term, it is necessary to study an appropriate operation simulation method, which can not only describe uncertainties in medium-and long-term objectively, but also provide effective support for medium-and long-term planning.

In order to achieve the goals above, some characteristics are summarized that a medium-and long-term operation simulation method need to possess as follows:

1) Take account of uncertainties in medium-and long-term reasonably and adequately [1], [5]. Different components of power system are likely to show different uncertainty characteristics, and sometimes uncertainty characteristics of medium-and long-term are different with characteristics of other periods. Besides, more components will show uncertainties in medium-and long-term comparing with short-term. Therefore, a reasonable and adequate consideration is necessary.
2) Provide as much servable information as possible [6]. Large amount of uncertainties in medium-and long-term bring difficulties to decision-making. More servable information will help to better assess medium-and long-term operation and find potential risks in operation process, and thus better support medium-and long-term planning.
3) Minimize computational effort [7]. For medium-and long-term planning, a long time study is usually necessary. Many uncertainties involved in modeling are likely to increase computational complexity, which is adverse to long time study.

There are few literatures completely focus on medium- and long-term power system operation. In these existing works, load duration curve based probabilistic production simulation (PPS) methods [7], [8] and scenario based unit commitment and/or economic dispatch (UCED) methods [9]–[13] are widely utilized. Li *et al.* [7] propose a non-sequential PPS model considering the uncertainty of power-only unit, combined heat and power unit and wind power, and greatly reduces computation time by fast Fourier transform and equivalent energy function method. Jiang *et al.* [8] propose a PPS method for system planning and consumption assessment in the medium and long-term time scale, and uncertainties of hydropower stations, renewable energies and forced outage of conventional units are taken into account. However, PPS is a non-sequential method and sequential characteristics of power system are difficult to describe, which means the analysis and evaluation of power system are relatively rough. Chen *et al.* [9] build an operation simulation model based on security-constrained unit commitment and consider the long-term uncertainties of wind, solar and load via the scenario tree using the Monte Carlo method. Simoglou *et al.* [10] utilize the Long-Term Scheduling model, which essentially is a scenario based UCED model, to consider uncertainties of renewable energy and realize mid-/long- term operation simulation. Helistö *et al.* [11] adopt a UCED model called JMM to analyze the long-term impact of wind, solar and demand side, and the uncertainties of RE are reflected by scenario tree tool. Bezerra *et al.* [12] build a stochastic long-term economic dispatch model for hydrothermal power system. This model considers uncertainty of hydropower generation prediction and thus obtains a large number of scenarios, and these scenarios are reduced by using k-means method. Despite UCED methods consider the uncertainties of RE and load by scenario method and can simulate with a relatively fast computational efficiency, the uncertainties of operating states in generation side and grid side are usually ignored, and if considered it will greatly increase scenario numbers and cause enormous computational efforts for solution. Besides the relatively large data requirements for UCED methods are also likely to pose challenges for medium-and long-term operation simulation. Furthermore, some researches are devoted to achieving the prediction of uncertainties in medium-and long-term [14], [15], and simulate operation condition based on the predicted results [16]. Apparently, by this method, operation simulation results are mainly depended on the precision of prediction, which will bring difficulties to appropriate and accurate decision-making. In addition to above methods, the universal generating function (UGF) based simulation methods are also applied to the medium-and long-term operation simulation in recent years. Jin *et al.* [17] build probabilistic distribution function of wind power and conventional generation units in order to describe uncertainty, and propose a UGF based PPS method to simulate long-term operation. Wang *et al.* [18] and Ding *et al.* [19] build uncertainty model of wind farm based on UGF method, in which the possible correlation between different wind turbines and the possible force outage are taken into account, and thus achieve the medium-and long-term operation simulation and assessment of power system with wind farm. From this we can find that UGF method can easily consider a large number of uncertainties and achieve medium-and long-term operation simulation with high efficiency, but in these methods, more components in power system need to be involved and state dependency need to be considered, what's more, some improvements should be adopted to avoid state explosion when system scale is large, and more servable information should be mined to better support planning. Comparing with medium-and long-term operation simulation, the number of literatures on short-term operation is relatively large. In these literatures, the great majority adopt UCED method for operation simulation [20], and they consider uncertainties by several methods such as predicting the uncertainty factors [21]–[23], stochastic programing [24], [25], robust optimization [26], [27] and interval optimization [28], [29]. However, the short-term methods are not fully applicable to medium-and long-term because of the insufficient consideration of uncertainties and huge computational effort.

In summary, despite for the convenience of considering uncertainties and the high computational efficiency, PPS method is a non-sequential method and the detailed analysis is unavailable; UCED is the mainstream method for operation simulation currently, and moderate amount of uncertainties are able to be considered efficiently, but the great amount of uncertainties in medium-and long-term operation simulation will bring challenges to this method; UGF method is able to consider large amount of uncertainties while keep a high computational efficiency, but it still needs to be improved in the aspect of comprehensiveness of uncertain factors, state dependency, state explosion of large scale system and supporting medium-and long-term planning.

To address the limitations above, this paper introduces the multi-state method to consider uncertainties of power system, and builds the multi-state probabilistic models of generation side, grid side, load side and energy storage. In combination with the multi-state model of each component, this paper builds a medium-and long-term operation simulation method based on UGF considering uncertainties of generation-grid-load-energy storage comprehensively. In order to deal with the state explosion problem of traditional method, the minimum distance classification method is adopted and computational efficiency is improved. Through in-depth mining of the results, some additional information such as change trend of LOLP and maximum power supply capacity of power system with different confidence probability can also be provided to find weak spots of system and better support the medium-and long-term planning. Besides, the suitable area of different operation simulation method is also discussed.

The remainder of this paper is organized as follows. Section II builds multi-state probabilistic models of main components in generation-grid-load-energy storage based on multi-state analysis method. By these models, section III proposes the improved UGF method and presents operation simulation process. Section IV verifies the validity of proposed method in IEEE RTS-79 and discusses the suitable area of different operation simulation method, and also applies this method to Zhangjiakou power system to prove the practicability. Section V gives the conclusions.

II. MULTI-STATE PROBABILISTIC MODELING OF GENERATION-GRID-LOAD-ENERGY STORAGE

In medium-and long-term, the operation condition of conventional units and the output of RE on generation side, flexible regulation of external transmission lines on grid side, demand response on load side as well as the charging and discharging process of energy storage facilities, all possess great uncertainties. The specific operation condition of each component is usually uncertain and shows multiple possible states, and mutual transformations among different states are also existed [32]. Therefore, the multi-state analysis method is necessary. Multi-state analysis method is an important method for uncertain system simulation and analysis. By considering uncertainties of all components and matching these uncertainties freely, simulation of uncertain system can be achieved. Because of the convenience of considering numerous uncertainties, multi-state analysis method is applied in many fields [30], [31]. Based on multi-state analysis method, this section builds multi-state probabilistic models to describe uncertainties in generation-grid-load-energy storage, and introduces Markov method to deal with state dependency.

A. CONVENTIONAL GENERATING UNIT

Conventional units mainly include run-of-river hydropower units, thermal power units, nuclear power units, etc. They show different uncertainty features according to their operating positions in the load curve. By and large, these units can be divided into base load units and peaking units.

1) BASE LOAD UNIT MODEL

This kind of units usually operate in base load at rated power and may break down at a probability. Thus only the uncertainties of the two states need to be considered and the multi-state probabilistic model can be expressed as:

$$P_i(t) = \begin{cases} 0, & p_{ro,i}(t) = p_{ro,i}^{FOR} \\ P_{Ni}, & p_{ro,i}(t) = 1 - p_{ro,i}^{FOR} \end{cases} \tag{1}$$

2) PEAKING UNIT MODEL

The main role of peaking units is peak shaving, and they need to change outputs in real time in response to the volatilities from RE and load. In general, a peaking unit may show planned outage, rating, ramp and derating state in operating process, and switch its state according to the need of system. Meanwhile, units are likely to change from rating and derating state to forced outage state, and faults can also be repaired. Thus, multiple states are involved in peaking units and the state dependencies are also existed in operating process [33]. In order to describe the process above, a 7 state model of the peaking unit is introduced, and the state transfer process is shown in Fig. 1.

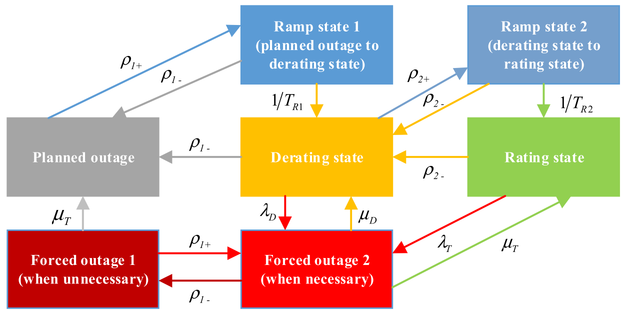

FIGURE 1. The multi-state model of a peaking unit.

These parameters in Fig. 1 can be calculated by imitating the calculation method of the 4-state model in Ref. [33]. To this end, Markov model can be formulated by the following expression:

$$\begin{bmatrix} p_{ro}^{P}(t+1), p_{ro}^{F1}(t+1), p_{ro}^{D}(t+1), p_{ro}^{F2}(t+1), \\ p_{ro}^{R1}(t+1), p_{ro}^{N}(t+1), p_{ro}^{R2}(t+1) \end{bmatrix} = \begin{bmatrix} p_{ro}^{P}(t), p_{ro}^{F1}(t), p_{ro}^{D}(t), p_{ro}^{F2}(t), \\ p_{ro}^{R1}(t), p_{ro}^{N}(t), p_{ro}^{R2}(t) \end{bmatrix} \cdot M(t) \tag{2}$$

where

$$p_{ro}^{P}(t)+p_{ro}^{F1}(t)+p_{ro}^{D}(t)+p_{ro}^{F2}(t)+p_{ro}^{R1}(t)+p_{ro}^{N}(t)+p_{ro}^{R2}(t)=1$$

The elements of $M(t)$ are as shown at the bottom of this page.

For convenience of calculation, the forced outage state 1, forced outage state 2, ramp state 1 and planned outage state which have similar values can be merged, and derating state and ramp state 2 can also be merged for the same reason. The multi-state probabilistic model of peaking unit can be expressed as:

$$P_i(t)=\begin{cases} 0, & p_{ro,i}(t)=p_{ro,i}^{F1}(t)+p_{ro,i}^{F2}(t)+p_{ro,i}^{R1}(t)+p_{ro,i}^{P}(t) \\ P_{de,i}, & p_{ro,i}(t)=p_{ro,i}^{D}(t)+p_{ro,i}^{R2}(t) \\ P_{Ni}, & p_{ro,i}(t)=p_{ro,i}^{N}(t) \end{cases} \tag{3}$$

B. WIND POWER UNIT

Due to the uncertainties of wind speed and units' fault, the output of wind power unit is likely to show multiple states in medium-and long-term operation. A Weibull distribution is

$$\begin{bmatrix} 1-\rho_{1+} & 0 & 0 & 0 & \rho_{1+} & 0 & 0 \\ \mu_T & 1-(\rho_{1+}+\mu_T) & 0 & \rho_{1+} & 0 & 0 & 0 \\ \rho_{1-} & 0 & 1-(\rho_{1-}+\rho_{2+}+\lambda_D) & \lambda_D & 0 & 0 & \rho_{2+} \\ 0 & \rho_{1-} & \mu_D & 1-(\rho_{1-}+\mu_D+\mu_T) & 0 & \mu_T & 0 \\ \rho_{1-} & 0 & \dfrac{1}{T_{R1}} & 0 & 1-\left(\rho_{1-}+\dfrac{1}{T_{R1}}\right) & 0 & 0 \\ 0 & 0 & \rho_{2-} & \lambda_T & 0 & 1-(\rho_{2-}+\lambda_T) & 0 \\ 0 & 0 & \rho_{2-} & 0 & 0 & \dfrac{1}{T_{R2}} & 1-\left(\rho_{2-}+\dfrac{1}{T_{R2}}\right) \end{bmatrix}$$

typically used for modelling wind speed variation considering long-term simulation [5]:

$$f(v) = \frac{k}{c} \cdot (\frac{v}{c})^{k-1} \cdot \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{4}$$

In addition, there is an approximate relationship between output and wind speed [3]:

$$P_i(t) = \begin{cases} 0, & v_i(t) < v_{in,i} or v_i(t) \geq v_{out,i} \\ P_{Ni} \cdot \dfrac{v_i(t) - v_{in,i}}{v_{Ni} - v_{in,i}}, & v_{in,i} \leq v_i(t) < v_{Ni} \\ P_{Ni}, & v_{Ni} \leq v_i(t) < v_{out,i} \end{cases} \tag{5}$$

Based on equivalent multi-state method, the wind turbine can be divided into several states according to capacity. Then through the inverse function of (5), corresponding wind speed interval of each state can be obtained. By putting each interval into (4), the probability of each interval, which is also the probability of each state, can be calculated. The process is shown in Fig. 2 and in conclusion, the uncertainty model of wind turbine considering forced outage can be expressed by (6).

$$P_i(t) = \begin{cases} 0, & p_{ro,i}(t) = p_{ro,i}^{FOR} + \left(1 - p_{ro,i}^{FOR}\right) \cdot p_{ro,i}^{1}(t) \\ & \vdots \\ P_i^k(t), & p_{ro,i}(t) = \left(1 - p_{ro,i}^{FOR}\right) \cdot p_{ro,i}^{k}(t) \\ & \vdots \\ P_{Ni}, & p_{ro,i}(t) = \left(1 - p_{ro,i}^{FOR}\right) \cdot p_{ro,i}^{N}(t) \end{cases} \tag{6}$$

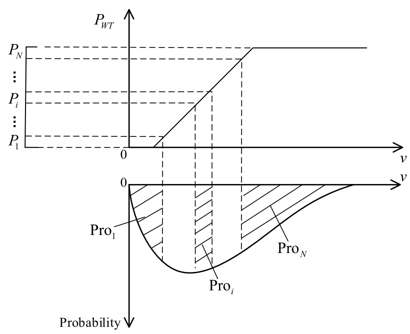

FIGURE 2. Brief process of calculating probability corresponding to each wind turbine output state.

C. PV POWER UNIT

Uncertainties of solar irradiation and units' fault are the main reasons for multiple states of PV power units. Solar irradiation is commonly characterized by Beta distribution function for long-term simulation [3]:

$$f(I) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) + \Gamma(\beta)} \cdot \left(\frac{I}{I_{\max}}\right)^{\alpha-1} \cdot \left(1 - \frac{I}{I_{\max}}\right)^{\beta-1} \tag{7}$$

An approximate relationship between output and solar irradiation is as follows:

$$P_i(t) = \begin{cases} P_{Ni} \cdot \dfrac{I_i(t)}{I_{\max}}, & I_i(t) \leq I_{\max} \\ P_{Ni}, & I_i(t) > I_{\max} \end{cases} \tag{8}$$

Similarly, by using equivalent multi-state method, PV unit can also be divided into several states according to capacity, then through the inverse function of (8), solar irradiation interval of each state can be obtained. In the end, probability of each solar irradiation interval, also the probability of each state, can be calculated by (7). Therefore, PV unit multi-state probabilistic model can be built as shown in (9).

$$P_i(t) = \begin{cases} 0, & p_{ro,i}(t) = p_{ro,i}^{FOR} + \left(1 - p_{ro,i}^{FOR}\right) \cdot p_{ro,i}^{1}(t) \\ & \vdots \\ P_i^k(t) \cdot ind(t), & \\ & p_{ro,i}(t) = \left(1 - p_{ro,i}^{FOR}\right) \cdot p_{ro,i}^{k}(t) \\ & \vdots \\ P_{Ni} \cdot ind(t), & \\ & p_{ro,i}(t) = \left(1 - p_{ro,i}^{FOR}\right) \cdot p_{ro,i}^{N}(t) \end{cases} \tag{9}$$

D. EXTERNAL TRANSMISSION LINE

In the modeling of grid side, external transmission line usually plays a key role in reliable operation for a region, while restrictive factors in the internal grid can be overcome by adjusting operation mode [34]. Transmission power of a transmission line is also uncertain in medium-and long-term. Usually in order to ensure the recovery of line investment, the transmission line will maintain a certain transmission capacity, but at the same time, it can also be adjusted according to the need of system. Similar to peaking units, transmission lines may also show rating state, derating state, ramp state and outage state with corresponding probabilities, and state dependency is also existing. Therefore, the transmission power of transmission line is divided into a fixed power and an adjustable power. Where the fixed power can be described by modifying load, and the adjustable one can be equivalent to a virtual power plant (VPP) with a minimum output of 0. The multi-state probabilistic model of adjustable power is shown in (10).

$$P_i(t) = \begin{cases} 0, & p_{ro,i}(t) = p_{ro,i}^{F1}(t) + p_{ro,i}^{F2}(t) \\ & \qquad + p_{ro,i}^{R1}(t) + p_{ro,i}^{P}(t) \\ P_{de,i}, & p_{ro,i}(t) = p_{ro,i}^{D}(t) + p_{ro,i}^{R2}(t) \\ P_{Ni}, & p_{ro,i}(t) = p_{ro,i}^{N}(t) \end{cases} \tag{10}$$

E. DEMAND RESPONSE

On demand side, this paper mainly considers the impact of DR. Due to uncertainties of power consumers' response ability, DR shows multiple states under a certain incentive and electricity price. For ease of modeling, DR model is divided into incentive-based demand response (IDR) model and price-based demand response (PDR) model.

1) IDR MODEL

IDR mainly influences peak load reductions. However, the reduction amount is uncertain in medium-and long-term and multiple amounts may occur with probabilities. Meantime, state dependency is also existing. Refer to peaking unit model, IDR can be equivalent to a type of VPP with a minimum output of 0, and the multi-state probabilistic model is as follows:

$$P_i(t)=\begin{cases}0, & p_{ro,i}(t)=p_{ro,i}^{F1}(t)+p_{ro,i}^{F2}(t)\\ & \quad +p_{ro,i}^{R1}(t)+p_{ro,i}^{P}(t)\\ P_{de,i}, & p_{ro,i}(t)=p_{ro,i}^{D}(t)+p_{ro,i}^{R2}(t)\\ P_{Ni}, & p_{ro,i}(t)=p_{ro,i}^{N}(t)\end{cases}\tag{11}$$

2) PDR MODEL

PDR mainly influence load transfer and the degree of load transfer is reflected by transfer rates. Usually they are uncertain and various according to the type of consumers. By calculating expected value of each transfer rate and then the modified load after implementation of PDR can be obtained by (12).

$$L(t)=\begin{cases}L_0(t)+\lambda_{p-v}\bar{L}_{peak}+\lambda_{f-v}\bar{L}_{flat}, & t\in T_{valley}\\ L_0(t)+\lambda_{p-f}\bar{L}_{peak}-\lambda_{f-v}\bar{L}_{flat}, & t\in T_{flat}\\ L_0(t)-\lambda_{p-f}\bar{L}_{peak}-\lambda_{p-v}\bar{L}_{peak}, & t\in T_{peak}\end{cases}\tag{12}$$

F. ENERGY STORAGE FACILITY

Energy storage facilities include pumped storage, battery energy storage, hydrogen energy storage, etc. According to the need of system, the operating state of them is uncertain in each period, and they will show 2 states: charging state when expected generating power is greater than load and discharging state when generating power is less. Meanwhile, energy storage facilities in discharging process can be considered as an equivalent generation unit, and are also likely to show multi-states.

1) CHARGING PROCESS

Charging capacity is affected by both certain and uncertain factors including maximum storage capacity, expected generating power of system, rated power of facility, etc. The expected charging capacity of energy storage facility can be expressed as follows:

$$G_t^{ch}=min\left\{\left(\frac{S_{SOC\,\max}-S_{SOC}(t)}{\Delta t}\right)\cdot\eta_{ch},\,G_{t,aver}^{ch}-L(t),\,P_s\right\}\tag{13}$$

In charging process, energy storage facilities can be regard as additional load, and total load is the sum of original load and expected charging power.

2) DISCHARGING PROCESS

In discharging process, energy storage facilities can be equivalent to a type of generation source, and discharging power of them can be regarded as installed capacity. Similarly, the equivalent installed capacity is influenced by: minimum storage capacity, rated power of facility, etc.

$$G_t^{dis}=min\left\{\left(\frac{S_{SOC}(t)-S_{SOC\,\min}}{\Delta t}\right)\cdot\eta_{dis},P_s\right\}\tag{14}$$

For convenience, regarding the average discharging power as power rating of equivalent unit, the multi-state probabilistic model in discharging process can be expressed as follows:

$$P_i(t)=\begin{cases}0, & p_{ro,i}(t)=p_{ro,i}^{FOR}\\ G_t^{dis}, & p_{ro,i}(t)=1-p_{ro,i}^{FOR}\end{cases}\tag{15}$$

III. POWER SYSTEM OPERATION SIMULATION BASED ON IMPROVED UNIVERSAL GENERATING FUNCTION

These multi-state probabilistic models of generation-grid-load-energy storage compose a complex multi-state system, and a simple and efficient multi-state analysis method is necessary for simulation and analysis. UGF is an important tool for multi-state system analysis and it is originally proposed by I. Ushakov in 1986 [35], [36]. By using UGF method, complex state combination process can be simplified greatly and simulation can be easily carried out. For this advantage, UGF has attracted more and more attention in recent years. In this section, brief introduction of UGF method and UGF based operation simulation method are given firstly, then an improvement strategy for avoiding state explosion is proposed, and finally the simulation process is put forward.

A. FUNDAMENTALS OF UGF METHOD

The main idea of UGF is as follows: firstly, discretize the continues state of each element in system, then introduce the operator z, and use z as the base and each discrete state as the exponent, and thus construct the UGF of an element. For an element with n states, the UGF can be formulated as:

$$u_1(z)=p_{ro,1}^1\cdot z^{x_1^1}+\cdots+p_{ro,1}^n\cdot z^{x_1^n}=\sum_{k=1}^{n}p_{ro,1}^k\cdot z^{x_1^k}\tag{16}$$

The joint probability distribution of two multi-state elements can be achieved by multiplication operations of the 2 UGFs:

$$\begin{aligned}u_{JPD}(z)&=\otimes\{u_1(z),u_2(z)\}\\ &=\sum_{i=1}^{n_1}\sum_{j=1}^{n_2}\left(p_{ro,1}^i\cdot p_{ro,2}^j\right)z^{x_1^i+x_2^j}=\sum_{k=1}^{n_{uni}}p_{ro,3}^k\cdot z^{x_3^k}\end{aligned}\tag{17}$$

In the same way, for a system with plenty of elements, the joint probability distribution of the system can also be acquired by continues multiplication operations of UGFs. Finally, by statistics on the states and corresponding probabilities we concerned, simulation of a system can be achieved. If endowed with sequential characteristic, the sequential UGF model can also be set up.

B. POWER SYSTEM OPERATION SIMULATION BASED ON UGF

The main process of UGF based simulation in one period is as follows: firstly, multiply the UGF of various components, and the joint probability distribution of power system can be calculated; then match the joint probability distribution with load in this period, and the expected generating energy of various units and reliability indices in corresponding period can be obtained. For different period, repeat the process above and these indices in all periods are able to be obtained.

In period t, the UGF of system containing the first m units can be expressed by (18).

$$u^{(m)}(z,t) = \otimes\{u_1(z,t), u_2(z,t), \cdots, u_m(z,t)\} = \sum_{k=1}^{n_{(m)}(t)} p^k_{ro,(m)}(t)\cdot z^{P^k_{(m)}(t)} \quad (18)$$

By comparing each output state $P^k_{(m)}(t)$ with load $L(t)$, and counting these state whose output is less than load, the reliability indices such as loss of load probability (LOLP) and expected energy not supply (EENS) of subsystem become available. When a new unit is put into operation, the change of EENS is the unit's expected generating capacity. Reliability indices of subsystem can be calculated as follows:

$$LOLP(m,t) = \sum_{P^k_{(m)}(t)<L(t)} pro^k_{(m)}(t) \quad (19)$$

$$EENS(m,t) = \sum_{P^k_{(m)}(t)<L(t)} p^k_{ro,(m)}(t)\cdot\left[L(t)-P^k_{(m)}(t)\right] \quad (20)$$

Furthermore, the maximum power supply capacity of the system containing the first m units can also be acquired by (21).

$$C^\theta_{\max}(t) = P^x_{(m)}(t), \quad x = \max\left\{x | \sum_{i=1}^{x} pro^x_{(m)}(t) \le 1-\theta\right\} \quad (21)$$

On this foundation, putting the $m+1$th unit into operation, the expected generating energy of this unit can formulated below.

$$E(m+1,t) = EENS(m,t) - EENS(m+1,t) \quad (22)$$

In particularly, the expected generating energy of the first unit is as follows:

$$E(1,t) = L(t) - EENS(1,t) \quad (23)$$

Putting new unit into operation one by one and calculating joint probability distribution of corresponding subsystem, and then utilizing (18) to (23), each expected generating energy can be determined. After all units being put into operation, the expected generating capacities of all units and the LOLP, EENS as well as the maximum power supply capacity of the entire power system can be find. Repeating the method above, the operation condition and reliability indices in various periods are obtained. Eventually, the LOLP of power system in the entire research cycle is the mean of LOLP in each period, the EENS is the sum of EENS in each period, and lose of load expectation (LOLE) can be calculated by multiplying LOLP and research cycle T.

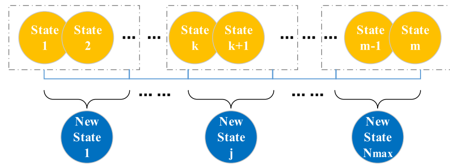

FIGURE 3. Minimum distance classification method.

C. IMPROVEMENT STRATEGY OF OPERATION SIMULATION

Obviously, with the increase of units and corresponding states, state amount of joint probability distribution will increase exponentially, and traditional treatment will make an extremely high request for computational capability and even cause the state explosion problem [25]. Therefore, it is essential to aggregate similar states in the course of calculating joint distribution.

By reasonably determining the maximum state number $N_{\max}$ and the center of each category in advance, and using minimum distance classification method to classify various states, the computation efficiency will be promoted greatly [37]. Thus the minimum distance classification method is adopted in this paper. Brief steps of improvement strategy are as follows:

Step 1: According to the determined maximum state number, as well as the maximum state and minimum state, the state series can be divided into some equidistant partition, and each partition center represents the state value of corresponding category.

Step 2: Calculate the distance from each state of original series to each category center, and group each state of original series into the nearest category.

Step 3: Add these probabilities that are classified into the same category, and take it as the probability of corresponding new state.

Following the improvement strategy, when calculating joint probability distribution, it is need to determine whether the state number of joint probability distribution exceeds $N_{\max}$, and implement the above steps if exceeds.

D. SIMULATION PROCESS

Usually the operation simulation is an optimization process, which includes the objective for minimizing operation cost and includes operation constraints of components and the system. Operation constraints of components such as conventional units are reflected in corresponding models and constraints of the system include electricity balance constraint and reliability constraint.

$$\min \sum_{i\in N, t\in T} E(i,t)\cdot Cost(i)$$
$$s.t. \begin{cases} \sum_{i\in N} E(i,t) = L(t)\cdot\Delta t \\ LOLP \le C \end{cases} \quad (24)$$

where the $E(i, t)$ and $LOLP$ can be calculated by (18)-(23). However, with the increasing number of generating units, the number of variables will also increase exponentially, and it will pose great challenges to calculate the optimal solution. Imitating the treatment for convolution in Ref. [7], the UGF based operation simulation can be also solved by numerical method.

In order to minimize the total cost, the operating order should be determined by operation cost. Considering influences of constraints especially the LOLP limit, RE cannot be fully utilized [38], so these unavailable RE units will have the lowest priority level in operation. In summary, the optimal operation order of all types of units from high to low is: baes load units, available wind turbines and PV units, peaking units, VPPs of external transmission line, VPPs of DR, unavailable wind turbines and PV units and energy storage facilities. Based on the optimal operation order, the operation simulation process is given below:

Step 1: Import original data, initialize parameters and build UGF of each component.

Step 2: According to the determined operating order, put each unit (or equivalent unit) successively except for energy storage facilities, and then calculate the initial joint distribution and expected generation energy of each unit in this period by improved UGF based operation method.

Step 3: Compare the expected generation energy of all units with load demand, and thus determine the working state of energy storage facilities.

Step 4: If the energy storage facilities are in charging state, calculate the charging energy and then modify the load curve, and simulate the operating process again; if the energy storage facilities are in discharging state, take them as equivalent units and continue to simulate; if the total generating energy is equal to demand, the facilities will not work.

Step 5: Calculate the reliability indices in this period, and update the stored energy of facilities for analysis in next period.

Step 6: Repeat step 2 to step 5, until all time periods are considered.

Step 7: Calculate LOLP and EENS of the whole research cycle.

IV. CASE STUDY

A. VALIDATION OF PROPOSED METHOD

The proposed method is verified in IEEE RTS-79. A Lenovo S5 (CPU: Core i5-7300HQ at 2.5GHZ, RAM: 16.0GB) is used as a computing platform and simulations are conducted by MATLAB R2018a. The study is carried out by comparing with PPS [39], UCED method adopted in Ref [7] as well as traditional UGF method [17], and the data are from Ref. [40].

1) ACCURACY ANALYSIS

Expected energy generations of all units are shown in Table 5 and LOLE and EENS of the 4 methods are shown in Table I. As can be seen, the relative errors of expected energy generation are small and all within 1.1%, and the relative errors of the 2 indices by proposed method are within 0.32% which are also acceptable, therefore the accuracy of proposed method is verified.

TABLE 1. LOLE and EENS of PPS, UCED, traditional UGF method and proposed method.

	PPS	UCED	Traditional UGF method	Proposed method
LOLE (h)	9.4385	9.4645	9.4342	9.4083
EENS (MWh)	1177.63	1161.72	1177.63	1177.63

Comparing sequential results of proposed method with UCED and relative errors are shown in Fig. 4. It can be seen that relative errors are within −5.1% to 7.4%, average error is about 0.32% and standard deviation of errors is 0.58%, and these errors are small. Therefore, the accuracy of proposed method is further verified.

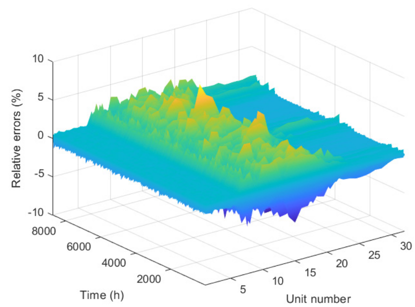

FIGURE 4. Relative errors of outputs of each unit in different periods.

2) COMPUTATIONAL EFFICIENCY ANALYSIS

In terms of computational efficiency, the computing time of PPS, UCED, traditional UGF method and proposed method are shown in Table II. The proposed method simplifies state combination process by improved UGF method, which avoids state explosion problem while retaining time series information, and in this way computational effort is greatly reduced. Comparing with traditional UGF method, the computational efficiency of proposed method has been improved by 27.24%. Comparing with UCED, the proposed method has an extremely high efficiency and the computing time is only 3.96% of UCED. While comparing with PPS, the proposed method does not sacrifice sequential characteristic. Although computing time of proposed method has increased when comparing with PPS, it is still within an acceptable range, and with the development of parallel computing technology, there is a large room for proposed method to improve computational efficiency.

In addition, by continuously increasing installed capacity of wind power unit, the computing time of traditional UGF method and proposed method is compared, as shown in Fig. 5.

TABLE 2. Computing time of PPS, UCED, traditional UGF method and proposed method.

	PPS	UCED	Traditional UGF method	Proposed method
Computing time (s)	0.9263	1320.7515	71.7983	52.2421

It can be seen that with the increase of wind power capacity, computing time of traditional UGF method increase rapidly and the average slope is about 0.104718 s/MW; while the computing time of proposed method increase relatively slow, and the average slope of proposed method is only 1/3 of traditional method. Therefore, the proposed method is able to improve computational efficiency to some extent. Besides, as the system scale increase, state number of the system will increase exponentially, and it is possible to exceed current computational capacity by traditional UGF method; while by using the proposed method, state number can be reduced continuously and state explosion can be avoided.

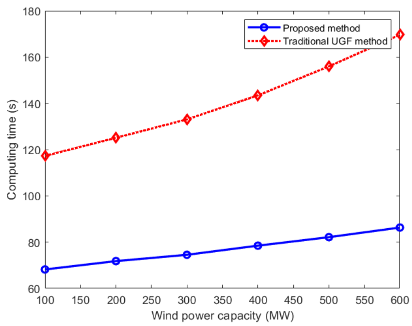

FIGURE 5. Computing time of traditional UGF method and proposed method.

3) ADDITIONAL INFORMATION AVAILABLE

Besides for power generation of each unit and total cost of power system, a medium-and long-term operation simulation method also needs to find weak spot of power system in the operation process, and thus better support medium-and long-term planning.

In the aspect of power system weak spots analysis, the proposed method can provide more servable information comparing with PPS and UCED. In response to global climate change, the generation capacity proportion of RE such as wind power keeps rising. To analyze the impact of growing RE generation on power system, this paper sets 4 scenarios: base scenario (IEEE RTS-79) in which no wind power is contained, scenario 1—replacing 100 MW conventional units by 100 MW wind turbines, scenario 2 and scenario 3 in which wind power proportion further increase and the replaced capacity reaches 200 MW and 300MW respectively. Change trends of LOLP in different scenarios are shown in Fig. 6:

In base scenario, there are 4 days with high LOLP level (not less than 0.01) in January, and the high LOLP hours mainly occurs in 17:00-18:00; from February to May, power system

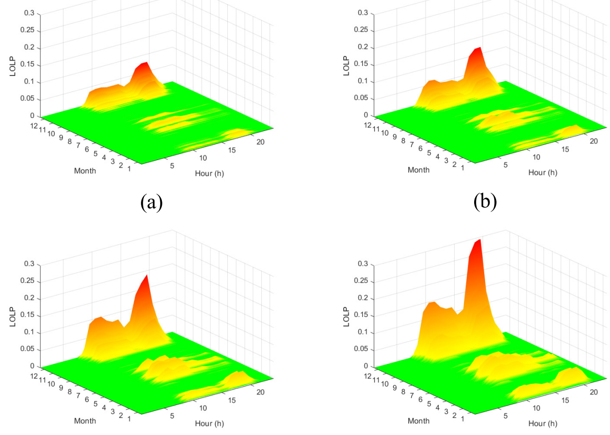

FIGURE 6. Change trend of LOLP: (a) base scenario, (b) scenario 1, (c) scenario 2, (d) scenario 3.

reliability is relatively high and almost no high LOLP hour exists; power shortage periods begin to appear in June and high LOLP periods are about 5 days, in which high LOLP hours are mainly from 11:00 to 15:00; system can maintain relatively high power supply reliability from July to October; however, power shortages begin to increase from November, and high LOLP hours increase from 17:00 -19:00 in early November to 9:00-14:00 and 16:00-20:00 in end of the year. However, in scenario 1, as the proportion of wind power increases, days of high LOLP rise to 8 and high LOLP hours extent to 17:00-19:00; moreover, power shortage months in spring and summer are also increase from May to July, and the high LOLP hours are also developed to 11:00-16:00; similarly, power shortages begin to increase from November, but comparing with base scenario, the high LOLP hour covers 9:00-21:00 in mid-late December. In scenario 2 and scenario 3, high LOLP days and hours will further increase with the increase of wind power proportion, which affect power system reliability significantly. Consequently, the proposed method is able to provide change trend of LOLP for medium- and long-term power system weak spots analysis, and it is an important superiority over other operation simulation methods.

In addition, comparing with other methods, the proposed method is also able to analyze the maximum power supply capacity under different confidence probabilities and grasp the overall power supply interval. Fig. 7 shows the maximum power supply capacities of different scenarios with a confidence probability of 99%. It can be found that due to the uncertainty of wind power, the maximum capacity shows volatility, and as the wind power proportion increase, power supply capacity keeps declining and the fluctuation range keeps expanding. Among these results, the average maximum power supply capacity for base scenario is about 2497MW and fluctuation range is close to 0; while from scenario 1 to scenario 3, the average values are 2420MW, 2348MW and

2276MW respectively, and corresponding fluctuation ranges extent to 20MW, 40MW and 60MW respectively. Increased wind power proportion leads to a lower system available capacity and the volatility of power supply capacity increase significantly. Therefore, besides the change trend of LOLP, proposed method can further provide power supply capacity interval for each period.

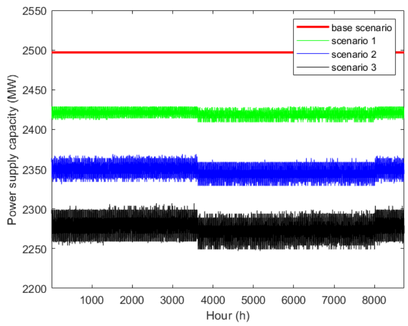

FIGURE 7. Maximum power supply capacity with confidence probability of 0.99 of different scenarios.

4) SUMMARY

Through the comparisons above, it is easy to see that PPS is hard to describe sequential operation conditions and it is not suitable for short-term simulation. Due to the simplicity and efficiency to consider uncertainties as well as the short computing time, PPS is suitable for a relatively rough simulation and analysis of medium-and long-term. UCED is able to describe time series condition of power system, and also to consider transmission constraints and small amount of uncertainties, thus it is very suitable for short-term study with small amount of uncertainties. But there are plenty of uncertainties in medium-and long-term, and computational efficiency of UCED will drop rapidly with the increase of uncertainties, which brings huge difficulty to medium-and long-term simulation. The proposed method builds probabilistic models based on multi-state analysis theory. For medium-and long-term analysis with extensive uncertainties, the proposed method is able to grasp various information objectively and provide more information of future, and thus better support medium-and long-term planning. In addition, the proposed method can also adapt the requirement of short-term simulation, but it shows insufficiency in consideration of transmission constraints when comparing with UCED. Table III summarizes characteristics of the 3 operation simulation methods.

TABLE 3. Characteristics of PPS, UCED and proposed method.

	PPS	UCED	Proposed method
Available information	☆	☆☆	☆☆☆
Computational efficiency	☆☆☆	☆	☆☆
Suitable area	medium-and long-term	short-term	medium-and long-term

B. ZHANGJIAKOU POWER SYSTEM

Zhangjiakou City lies in North China and it is the only one RE representative area of China to date. In recent years, wind power installed capacity in Zhangjiakou increase rapidly, which brings great challenges to safe and reliable operation of Zhangjiakou power system. Therefore, it is necessary to analyze operation condition of Zhangjiakou system, find weak spots and thus better guide future development. According to Zhangjiakou 2025 planning results, the total electric energy demand is about 18.774TWh, and total installed generation capacity is about 34.4GW, of which wind power installed capacity is about 20.5GW and the proportion is about 59.6%. Table IV shows the annual reliability indices and wind energy curtailment situation by proposed method. It can be seen that the overall reliability is relatively low, and LOLE is about 17.87 hours which is higher than the current national average level of 16.27 hours. Meanwhile, wind curtailment situation is extremely serious, annual wind curtailment is 9.0838TWh and curtailment ratio is 18.24%, which is also much higher than the 5% level required by China. These results are very close to the predictions of Zhangjiakou Power Grid Company and have been accredited by the operators.

TABLE 4. Reliability indices and wind energy curtailment situation in Zhangjiakou.

LOLP	LOLE (h)	EENS (GWh)	Wind Energy Curtailment (TWh)	Wind Energy Curtailment ratio (%)
0.00204	17.87	2.9919	9.0838	18.24

Fig. 8 shows the LOLP change trend of Zhangjiakou power system. The high LOLP days are mainly concentrated in June-August and November-December. Among them, the higher load level and greater uncertainty of wind speed in June-August than in other periods is the main reason for the high LOLP; affected by winter heating, the lack of power system flexibility in November-December also contributes to high LOLP. In addition, among these periods above, the high LOLP hours are mainly concentrated between 19:00 and 21:00 for each day, and it is caused by the evening peak of load and the lack of reliable and flexible power supply. Therefore, it is necessary to improve power supply capacity and increase flexibility for these periods.

Zhangjiakou power system's maximum power supply capacity with confidence probability of 99% is shown in Fig. 9. It can be seen that the maximum power supply capacity fluctuates in interval [8.4876, 13.6189] GW. Go through the whole year, the maximum power supply capacity reaches peak value for the good wind condition and adequate peaking capacity of system in spring, while reduce to the valley value due to heating supply in the second half of autumn and winter.

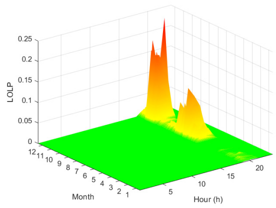

FIGURE 8. Change trend of LOLP.

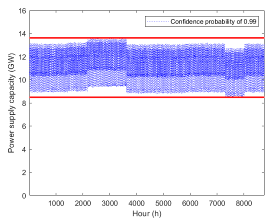

FIGURE 9. Maximum power supply capacity of Zhangjiakou power system.

V. CONCLUSION

The large number of uncertainties in generation-grid-load-energy storage in medium-and long-term bring challenges to medium-and long-term planning, in order to better support planning, an appropriate operation simulation method is necessary. In this paper, a medium-and long-term operation simulation method based on improved UGF is proposed. In order to describe uncertainties in medium-and long-term, this paper builds multi-state probabilistic models for the main components in generation-grid-load-energy storage and adopts Markov method to reflect state dependency in operating process. Take consideration of the possible state explosion of traditional UGF based simulation, this paper utilizes the minimum distance classification method to decrease the state numbers. Correctness and superiorities of the proposed method is verified in IEEE RTS-79 by comparing with PPS, UCED as well as traditional UGF method, and the practicality of proposed method is presented in the case study of Zhangjiakou. By the proposed method, a relatively high computational efficiency can be obtained and sequential trend of LOLP and maximum power supply capacity can be provided to better support medium-and long-term planning.

The suitable areas of proposed method, PPS and UCED are also discussed. PPS is suitable for rough medium-and long-term simulation and analysis, and UCED is suitable for short-term operation simulation. For the proposed method, it is mainly applied to medium-and long-term analysis, while for short-term analysis, it is also applicable when transmission constraints are relatively simplified.

However, there are still some aspects of this method that need to be improved. In terms of modeling, the differences of wind speed (or solar irradiation) between different units in wind farm (or PV power station) are neglected in this paper, and the average level is used for simplicity; moreover, only the randomness of power system is considered, and in future study more uncertainties such as fuzziness and roughness can be considered. Besides, parallel computing technology can also be utilized to further promote computational efficiency.

APPENDIX

TABLE 5. Expected energy generation of each unit by PPS, UCED, traditional UGF method and proposed method.

Unit No.	Capacity (MW)	Expected energy generation (GWh)			
		Proposed method	PPS method	UCED method	Traditional UGF Method
1	50	432.432	432.432	432.437	432.432
2	50	432.432	432.432	432.417	432.432
3	50	432.432	432.432	432.448	432.432
4	50	432.432	432.432	432.429	432.432
5	50	432.432	432.432	432.428	432.432
6	50	432.432	432.432	432.439	432.432
7	400	3075.072	3075.072	3074.644	3075.072
8	400	3067.694	3067.694	3068.071	3067.694
9	350	2524.747	2524.747	2524.848	2524.747
10	155	964.245	964.245	964.162	964.245
11	155	834.321	834.321	833.994	834.321
12	155	681.439	681.439	681.433	681.439
13	155	531.327	531.327	531.417	531.327
14	76	218.672	218.672	218.738	218.672
15	76	187.007	187.007	187.018	187.007
16	76	154.826	154.826	154.776	154.826
17	76	123.791	123.791	123.806	123.791
18	197	197.215	197.215	197.413	197.215
19	197	97.069	97.069	97.186	97.069
20	197	40.809	40.809	40.752	40.809
21	100	9.89	9.89	9.874	9.890
22	100	5.676	5.676	5.666	5.676
23	100	3.126	3.126	3.128	3.126
24	12	0.269	0.269	0.269	0.269
25	12	0.248	0.248	0.249	0.248
26	12	0.229	0.229	0.23	0.229
27	12	0.211	0.211	0.212	0.211
28	12	0.194	0.194	0.196	0.194
29	20	0.266	0.266	0.269	0.266
30	20	0.233	0.234	0.236	0.234
31	20	0.205	0.206	0.207	0.206
32	20	0.181	0.182	0.182	0.182

REFERENCES

[1] N. E. Koltsaklis and A. S. Dagoumas, "State-of-the-art generation expansion planning: A review," *Appl. Energy*, vol. 230, pp. 563–589, Nov. 2018.
[2] H. T. Jadhav and R. Roy, "Stochastic optimal power flow incorporating offshore wind farm and electric vehicles," *Int. J. Elect. Power Energy Syst.*, vol. 69, pp. 173–187, Jul. 2015.
[3] A. R. Jordehi, "How to deal with uncertainties in electric power systems? A review," *Renew. Sustain. Energy Rev.*, vol. 96, pp. 145–155, Nov. 2018.
[4] M. Aien, A. Hajebrahimi, and M. Fotuhi-Firuzabad, "A comprehensive review on uncertainty modeling techniques in power system studies," *Renew. Sustain. Energy Rev.*, vol. 57, pp. 1077–1089, May 2016.

[5] K. N. Hasan, R. Preece, and J. V. Milanović, "Existing approaches and trends in uncertainty modelling and probabilistic stability analysis of power systems with renewable generation," *Renew. Sustain. Energy Rev.*, vol. 101, pp. 168–180, Mar. 2019.

[6] S. Collins, J. P. Deane, K. Poncelet, E. Panos, R. C. Pietzcker, E. Delarue, and B. P. Ó. Gallachóir, "Integrating short term variations of the power system into integrated energy system models: A methodological review," *Renew. Sustain. Energy Rev.*, vol. 76, pp. 839–856, Sep. 2017.

[7] H. Li, Z. Lu, Y. Qiao, and N. Wang, "A non-sequential probabilistic production simulation method for wind energy curtailment evaluation considering the seasonal heat supply constraints," *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 462–473, Jan. 2018.

[8] J. Jiang, Y. Qiao, and Z. Lu, "The probabilistic production simulation for renewable energy power system considering the operation of cascade hydropower stations," in *Proc. Int. Conf. Power Syst. Technol. (POWERCON)*, 2018, pp. 331–338.

[9] Z. Chen, L. Wu, and M. Shahidehpour, "Effective load carrying capability evaluation of renewable energy via stochastic long-term hourly based SCUC," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp. 188–197, Jan. 2015.

[10] C. K. Simoglou, E. A. Bakirtzis, P. N. Biskas, and A. G. Bakirtzis, "Probabilistic evaluation of the long-term power system resource adequacy: The Greek case," *Energy Policy*, vol. 117, pp. 295–306, Jun. 2018.

[11] N. Helistö, J. Kiviluoma, and H. Holttinen, "Long-term impact of variable generation and demand side flexibility on thermal power generation," *IET Renew. Power Gener.*, vol. 12, no. 6, pp. 718–726, Apr. 2018.

[12] B. Bezerra, Á. Veiga, L. A. Barroso, and M. Pereira, "Stochastic long-term hydrothermal scheduling with parameter uncertainty in autoregressive streamflow models," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 999–1006, Mar. 2017.

[13] A. Helseth, B. Mo, A. L. Henden, and G. Warland, "Detailed long-term hydro-thermal scheduling for expansion planning in the Nordic power system," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 2, pp. 441–447, 2018.

[14] S. Han, Y.-H. Qiao, J. Yan, Y.-Q. Liu, L. Li, and Z. Wang, "Mid-to-long term wind and photovoltaic power generation prediction based on copula function and long short term memory network," *Appl. Energy*, vol. 239, pp. 181–191, Apr. 2019.

[15] Z. Zhang, H. Qin, L. Yao, J. Lu, and L. Cheng, "Interval prediction method based on Long-Short Term Memory networks for system integrated of hydro, wind and solar power," *Energy Procedia*, vol. 158, pp. 6176–6182, Feb. 2019.

[16] Q. Zhang, M. Wang, X. Wang, and S. Tian, "Mid-long term optimal dispatching method of power system with large-scale wind-photovoltaic-hydro power generation," in *Proc. IEEE Conf. Energy Internet Energy Syst. Integr. (EI2)*, Nov. 2017, pp. 1–6.

[17] T. Jin, M. Zhou, and G. Li, "Universal generating function based probabilistic production simulation for wind power integrated power systems," *J. Mod. Power Syst. Clean Energy*, vol. 5, no. 1, pp. 134–141, 2017.

[18] P. Wang, L. Goel, Y. Ding, L. P. Chang, and M. Andrew, "Reliability-based long term hydro/thermal reserve allocation of power systems with high wind power penetration," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2009, pp. 1–7.

[19] Y. Ding, P. Wang, L. Goel, P. C. Loh, and Q. Wu, "Long-term reserve expansion of power systems with high wind power penetration using universal generating function methods," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 766–774, May 2011.

[20] H. Wu, "Stochastic multi-timescale power system operations with variable wind generation," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3325–3337, Sep. 2017.

[21] A. Khodaei, M. Shahidehpour, L. Wu, and Z. Li, "Coordination of short-term operation constraints in multi-area expansion planning," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 2242–2250, Nov. 2012.

[22] X. Li and C. Jiang, "Short-term operation model and risk management for wind power penetrated system in electricity market," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 932–939, May 2011.

[23] B. Lu and M. Shahidehpour, "Short-term scheduling of battery in a grid-connected PV/battery system," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1053–1061, May 2005.

[24] C. G. Baslis, S. E. Papadakis, and A. G. Bakirtzis, "Simulation of optimal medium-term hydro-thermal system operation by grid computing," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1208–1217, Aug. 2009.

[25] A. Tuohy, P. Meibom, E. Denny, and M. O'Malley, "Unit commitment for systems with significant wind penetration," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 592–601, May 2009.

[26] R. Jiang, J. Wang, and Y. Guan, "Robust unit commitment with wind power and pumped storage hydro," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 800–810, May 2012.

[27] G. Morales-España, Á. Lorca, and M. M. de Weerdt, "Robust unit commitment with dispatchable wind power," *Electr. Power Syst. Res.*, vol. 155, pp. 58–66, Feb. 2018.

[28] L. Wu, M. Shahidehpour, and Z. Li, "Comparison of scenario-based and interval optimization approaches to stochastic SCUC," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 913–921, May 2012.

[29] Y. Liu, M. Li, H. Lian, X. Tang, C. Liu, and C. Jiang, "Optimal dispatch of virtual power plant using interval and deterministic combined optimization," *Int. J. Elect. Power Energy Syst.*, vol. 102, pp. 235–244, Nov. 2018.

[30] J. Huang and M. J. Zuo, "Dominant multi-state systems," *IEEE Trans. Rel.*, vol. 53, no. 3, pp. 362–368, Sep. 2004.

[31] C. D. Dao and M. J. Zuo, "Reliability analysis of multi-state systems with s-dependent components," in *Proc. Annu. Rel. Maintainability Symp. (RAMS)*, Jan. 2015, pp. 1–6.

[32] A. Shrestha, L. Xing, and Y. Dai, "Decision diagram based methods and complexity analysis for multi-state systems," *IEEE Trans. Rel.*, vol. 59, no. 1, pp. 145–161, Mar. 2010.

[33] Y. Liu and M. Ding, "The comprehensive evaluation of the static and dynamic benefits of storage plant," *Automat. Electric Power Syst.*, vol. 18, no. 9, pp. 30–35, 1994.

[34] G. Li, G. Li, and M. Zhou, "Model and application of renewable energy accommodation capacity calculation considering utilization level of inter-provincial tie-line," *Protection and Control Modern Power Syst.*, vol. 4, no. 1, 2019, Art. no. 1.

[35] G. Levitin and A. Lisnianski, "Multi-state system reliability analysis and optimization (universal generating function and genetic algorithm approach)," in *Handbook of Reliability Engineering*, H. Pham, Ed. London, U.K.: Springer, 2003, pp. 61–90.

[36] A. Lisnianski, I. Frenkel, and Y. Ding, Eds., "Universal generating function method," in *Multi-state System Reliability Analysis and Optimization for Engineers and Industrial Managers*. London, U.K.: Springer, 2010, pp. 143–200.

[37] H. Lin and A. N. Venetsanopoulos, "A weighted minimum distance classifier for pattern recognition," in *Proc. Can. Conf. Elect. Comput. Eng.*, vol. 2, Sep. 1993, pp. 904–907.

[38] H. Zhang, Y. Yin, H. Shen, J. He, and S. Zhao, "Peak-load regulating adequacy evaluation associated with large-scale wind power integration," *Proc. CSEE*, vol. 33, no. 22, pp. 26–31, 2011.

[39] X. Wang, "Equivalent energy function approach to power system probabilistic modeling," *IEEE Trans. Power Syst.*, vol. PWRS-3, no. 3, pp. 823–829, Aug. 1988.

[40] P. Subcommittee, "IEEE reliability test system," *IEEE Trans. Power App. Syst.*, vol. PAS-98, no. 6, pp. 2047–2054, Nov. 1979.

ZHEYU GUO received the B.S. degree in electrical engineering from North China Electric Power University, China, in 2017, where he is currently pursuing the master's degree in electrical engineering. His main research interest includes power system operation and planning with large-scale renewable energy.

YANAN ZHENG (M'09) received the B.S., M.S., and Ph.D. degrees in electrical engineering from North China Electricity Power University in 2005, 2007, and 2011, respectively. He is currently an Associate Research Fellow with the Energy Research Institute, Chinese Academy of Macroeconomic Research. His main research interests include power system operation and planning, power system analysis and control, and energy economy.

GENGYIN LI (M'03) received the B.S., M.S., and Ph.D. degrees in electrical engineering from North China Electricity Power University, China, in 1984, 1987, and 1996, respectively. Since 1987, He has been with the School of Electrical and Electronic Engineering, North China Electric Power University, where he is currently a Professor. His main research interests include power system operation and planning, HVDC technology, power quality analysis and control, and new transmission and distribution technologies.