

Probabilistic production simulation of a power system with wind power penetration based on improved UGF techniques

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Abstract Universal Generating Function (UGF) techniques have been applied to Multi-State System (MSS) reliability analysis, such as long term reserve expansion of power systems with high wind power penetration. However, using simple steady-state distribution models for wind power and large generating units in reliability assessment can yield pessimistic appraisals. To more accurately assess the power system reliability, UGF techniques are extended to dynamic probabilistic simulation analysis on two aspects of modelling improvement. Firstly, a principal component analysis (PCA) combined with a hierarchal clustering algorithm is used to achieve the salient and time-varying patterns of wind power, then a sequential UGF equivalent model of wind power output is established by an apportioning method. Secondly, other than the traditional two-state models, the conventional generator UGF equivalent model is established as a four discrete-state continuous-time Markov model by L_z -transform. In the construction process of such a UGF model, the state values are transformed into the integral multiples of one common factor by choosing proper common factors, thus effectively restraining the exponential growth of its state number and alleviating the explosion thereof. The method is suitable for reliability assessment with dynamic probabilistic distributed random

variables. In addition, by acquiring the clustering information of wind power, the system reliability indices, such as fuel cost and CO₂ emissions through different seasons and on different workdays, are calculated. Finally, the effectiveness of the method is verified by a modified IEEE-RTS 79 system integrated with several wind farms of historical hourly wind power data of Zhangbei wind farm in North China.

Keywords Multi-state system, Reliability, Universal Generating Function (UGF), Probabilistic production simulation, Wind power

1 Introduction

Compared with Monte Carlo simulation techniques [1–4] and analytical methods [5–8], an Universal Generating Function (UGF) technique [9, 10] is the most promising analysis tool for the probabilistic production simulation of power systems, and has been widely used in the probabilistic production simulation analysis of power systems.

However, the main restriction of this powerful technique is that, theoretically it can only deal with random variables, and can only obtain the steady-state performance distributions of wind power and conventional generators. By using a basic UGF technique, it is impossible to analyze the dynamic probability distribution modes of reliability systems, including component aging reliability models, and non-stationary stochastic process of wind power under diurnal and seasonal pattern features, etc. Besides, there has been a number explosion in states of large systems. In this paper, two aspects of UGF modelling improvement are presented. On UGF modelling aspect of wind power, a hierarchal clustering method for constructing the time-variance UGF is proposed according to the non-stationary stochastic characteristics of wind power. Firstly, principal

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component analysis (PCA) [11] combined with a hierarchal clustering algorithm [12] is adopted to obtain the typical time-sequential samples of wind power output. An apportioning method [13] is used to establish the sequential UGF of the wind power output.

Besides the wind power output, the outputs of conventional generating units are not uniformly distributed too. Reference [14] proposed a multi-state Markov model for a coal-fired power generating unit, and a technique for the estimation of transition intensities between the various generating capacity levels of the unit based on the actual measurements. The technique can be used to estimate the dynamic distributions of generating capacity distribution. Based on the technique, the UGF of the conventional generating unit is formulated as a sequential UGF with an Lz -transform, which can express the time-varying multi-state Markov process as an UGF equivalent model [15]. The sequential UGF models for conventional generators reflect the impact of time-varying factors in operation and repair after failures. As a result, each component in power systems is formulated as a sequential UGF model, which will extend the UGF technique applicability to dynamic probabilistic production simulation analysis.

Furthermore, state values expressed as a multiple of the common factor, can avoid the exponential growth of the state combination number, thus the problem of number explosion of states is avoided in the proposed method. Finally, the proposed approach presents the ability to quantify the impact of the temporal correlation between wind power and load on the assessment of system reliability indices, fuel cost and CO₂ emissions.

The rest of the paper is organized as follows. The UGF technique is briefly summarized in Section 2. The reliability modelling of wind farms, conventional generating units, loads and system is presented with UGF technique in Section 3. The procedure of power system reliability assessment based on the dynamic probability distribution of the conventional generator and different patterns of wind farm or loads is proposed in Section 4. Case studies are provided in Section 5, followed by the conclusions in Section 6.

2 UGF technique

UGF technique is to find MSS reliability measures by using Ushakov's Universal generating Operator (UGO) Ω_f acting on the collection of the individual UGFs expression of all the individual random variables [10].

2.1 UGF expression

The basis of the UGF technique is to express the random variables as UGF expressions after z transform. Supposing

that there are two discrete random variables X_1 and X_2 , the corresponding probability function is:

$$\begin{cases} \Pr\{X_1 = x_{1i}\} = p_{1i}, & 1 \leq i \leq k_1 \\ \Pr\{X_2 = x_{2i}\} = p_{2i}, & 1 \leq i \leq k_2 \end{cases} \quad (1)$$

where x_{1i} is the i -th state of X_1 , and the corresponding probability is p_{1i} ; x_{2i} is the i -th state of X_2 , and the corresponding probability is p_{2i} ; k_1 and k_2 are the state numbers of X_1 and X_2 . After z transform, the corresponding UGF becomes:

$$\begin{cases} z\{x_1\} = u_{x_1}(z) = \sum_{i=1}^{k_1} p_{1i}z^{x_{1i}} = p_{11}z^{x_{11}} + p_{12}z^{x_{12}} + \dots + p_{1k_1}z^{x_{1k_1}} \\ z\{x_2\} = u_{x_2}(z) = \sum_{j=1}^{k_2} p_{2j}z^{x_{2j}} = p_{21}z^{x_{21}} + p_{22}z^{x_{22}} + \dots + p_{2k_2}z^{x_{2k_2}} \end{cases} \quad (2)$$

where $u_{x_1}(z)$ and $u_{x_2}(z)$ are the UGFs of X_1 and X_2 ; z has no substantial meaning.

The UGF expression provides a way to distinguish the values of random variables from the corresponding probability with z transform. The z transform can be extended to the UGO Ω_f for a function that concludes random variables.

Supposing that Y is an arbitrary function of x_1 and x_2 , so $Y = f(x_1, x_2)$. The z transform $u_Y(z)$ for Y can be formally obtained as a product of individual z transforms of x_1 and x_2 by the UGO Ω_f :

$$\begin{aligned} z\{Y\} = u_Y(z) &= \sum_{j=1}^K q_j z^{y_j} = \Omega_f\{u_1(z), u_2(z)\} \\ &= \sum_{j_1=1}^{k_1} \sum_{j_2=1}^{k_2} p_{1j_1} p_{2j_2} z^{f(x_{1j_1}, x_{2j_2})} \end{aligned} \quad (3)$$

where $q_j = \{q_1, q_2, \dots, q_K\}$ and $y_j = \{y_{j1}, y_{j2}, \dots, y_{jK}\}$ are the resulting probability mass function and the i -th state of random variable Y , respectively.

2.2 Sequential UGFs for time-varying process

For a function $Y(t) = f(x_1(t), x_2(t), \dots, x_m(t))$, which concludes discrete-state continuous-time random variables $x_1(t), x_2(t), \dots, x_m(t)$, z transform is extended to Lz -transform as [15]:

$$\begin{aligned} L_z\{Y(t)\} = u_Y(z, t, p_0) &= \sum_{j=1}^K q_j(t) z^{y_j(t)} \\ &= \Omega_f\{u_{x_1}(z, t), u_{x_2}(z, t), \dots, u_{x_m}(z, t)\} \\ &= \sum_{j_m=1}^{k_m} \dots \sum_{j_2=1}^{k_2} \sum_{j_1=1}^{k_1} p_{1j_1}(t) p_{2j_2}(t) \dots p_{mj_m}(t) z^{f(x_{1j_1}(t), x_{2j_2}(t), \dots, x_{mj_m}(t))} \end{aligned} \quad (4)$$



where $p_{1i}(t), p_{2i}(t), \dots, p_{mi}(t)$ are the probability of $x_1(t), x_2(t), \dots, x_m(t)$ at period t for any given initial states probability p_0 .

Straightforward computation of the probability mass function (p.m.f.) of $Y(t)$ using (4) is based on an enumerative approach. This approach is extremely resource consuming. Fortunately, there are two effective ways to reduce the computational burden: similar-terms collection and a recursive procedure [10].

The UGFs inherit the essential property of regular polynomials: they allow for collecting similar terms. If a UGF representing the p.m.f. of a random variable X contains the terms $p_h z^{x_h}$ and $p_m z^{x_m}$ for which $x_h = x_m$, the two terms can be replaced by a single term $(p_h + p_m) z^{x_m}$. Due to the feature, a reasonable common capacity factor Δc is chosen; and then, all of the state values, including wind generators, conventional generators and loads, are chosen as integer multiples of Δc ; finally, the identical states are merging. Therefore, the number of states is prevented from increasing exponentially with the improved UGF technique for the reliability assessment of power systems.

3 Reliability modelling with UGF technique

3.1 Reliability model for wind farms

3.1.1 Feature extraction technology of wind power and clustering algorithm

The transformation of wind speed to wind power involves a cubic relationship, if there is an error in the construction of wind speed model, the error in the construction of wind power model will be three times greater [16]. And then the wind power output model of wind farms is established by using wind power data. By a principal component feature extraction technology [11] and a hierarchical clustering algorithm [12], it shows that the representative samples of wind power from historical time series, and then the UGF equivalent of wind farms is expressed as time variant according to the patterns after clustering.

According to [12], a day can be taken as a clustering time unit. Because of inhomogeneities in the measurement data, this hierarchical clustering algorithm combined with PCA feature extraction technology is applied to achieving the patterns of wind power. PCA can be used to identify the patterns from the data, and to express the data in a way that highlights their similarities and differences. PCA is a useful tool for dealing with large data sets, in which extracting the features becomes an important step.

PCA method is suitable for feature extraction of wind power output. Supposing that there are p variables in the time series of wind power: x_1, x_2, \dots, x_p . A p -dimensional random vector x constituted by p variables as $x = (x_1, x_2, \dots, x_p)$. Supposing x can be linearizedly transformed as follows:

$$\begin{cases} y_1 = \mu_{11}x_1 + \mu_{12}x_2 + \mu_{1p}x_p \\ y_2 = \mu_{21}x_1 + \mu_{22}x_2 + \mu_{2p}x_p \\ \vdots \\ y_p = \mu_{p1}x_1 + \mu_{p2}x_2 + \mu_{pp}x_p \end{cases} \quad (5)$$

where y_1, y_2, \dots, y_p are linear combinations of x_1, x_2, \dots, x_p . In (5), every vector $\mu_i = (\mu_{i1}, \mu_{i2}, \dots, \mu_{ip})$ is a unit vector. And y_1 has the largest variance of linear combinations of x_1, x_2, \dots, x_p ; y_2 exhibits the largest variance of linear combinations unrelated to y_1 ; y_p has the largest variance of linear combinations unrelated to y_1, y_2, \dots, y_{p-1} . So y_1, y_2, \dots, y_p are called the first, second, ..., p -th main components of the original variables.

According to the significances of the main components, the weaker component (i.e., those with smaller variance) can be removed. Supposing that we obtain $q (q \leq p)$ main components, i.e., q orthogonal variables, so the original wind power output is mapped into a much smaller space, thus resulting in a concomitant dimension reduction. The value of main component q is determined by cumulative contribution rate. If the cumulative contribution rate exceeds 85%, the information in the original variables can be sufficiently reflected, and the corresponding q refers to the main components extracted in q . Firstly, the wind power data are clustering after feature extraction and each object forms a separate group. Secondly, similar groups are merging until only one group is left or the termination conditions are met. The similarity, which is the basis of similar measurement clustering, is performed by using the Euclidean distance:

$$d_{ij} = \sqrt{\sum_{k=1}^q (P_{wi}(k) - P_{wj}(k))^2} \quad (6)$$

where P_{wi} and P_{wj} are wind power vectors containing q main components.

Let D be the number of days studied, and R_w be the number of wind power output patterns, denoted by $1, 2, \dots, r_w, \dots, R_w$. The number of wind power outputs of pattern r_w is N_{r_w} , so the probability of pattern r_w is $\alpha_{r_w} = N_{r_w}/D$.

The R_w wind power patterns is obtained using a hierarchical clustering algorithm combined with principal component-feature extraction technology with probability α_{r_w} , denoted by $(r_w, \alpha_{r_w}) (r_w \in \{1, 2, \dots, R_w\})$.

3.1.2 UGF equivalent of wind farm

Each pattern of wind power is partitioned into H sub-periods, and an hourly resolution ($H = 24$) is adopted.

Modelling UGF for wind power in different sub-periods with apportioning method [13], supposing that all wind power output curves of wind power pattern r_w are shown in Fig. 1, and the number of curves is N_{r_w} , so each interval has N_{r_w} wind power values. We can obtain state values and the corresponding probabilities of each interval using the apportioning method. Supposing that the i -th wind farm has k_w states in pattern r_w in sub-period t , the UGF becomes:

$$u_i^w(z, t) = \sum_{j_w=1}^{k_w} p_{i,j_w}^w(t) z^{WP_{i,j_w}(t)} \quad (7)$$

where $WP_{i,j_w}(t)$ and $p_{i,j_w}^w(t)$ are wind power output and the corresponding probability of the i -th wind farm in state j_w , respectively.

From (7), it can be seen that the UGF equation of wind power is expressed as timing variations form, so the improved UGF can reflect the dynamic probabilistic distribution of wind power.

3.2 Reliability model for conventional generation units

A reliability model for the traditional conventional generators is established according to historical statistical data, but in actual systems, the failure rate is time-varying. The reliability model of the conventional generation unit is presented as a discrete-state continuous-time Markov process in this paper. Supposing that the states of the i -th conventional generator can be represented as the following polynomial [14]:

$$P_i^m(t) = \langle p_{i,j_m}^m, A_i^m, p_0^m \rangle \quad (8)$$

where p_{i,j_m}^m is the probability of a conventional generator i in state j_m , A_i^m is the transition probability intensities matrix, and p_0^m is the initial state probability vector of the conventional generator i .

Lz -transform of a discrete-state continuous-time Markov process of (8) is a UGF defined as [15]:

$$Lz\{P_i^m(t)\} = u_i^m(z, t, p_0) = \sum_{j_m=1}^{k_m} p_{i,j_m}^m(t) z^{P_{i,j_m}(t)} \quad (9)$$

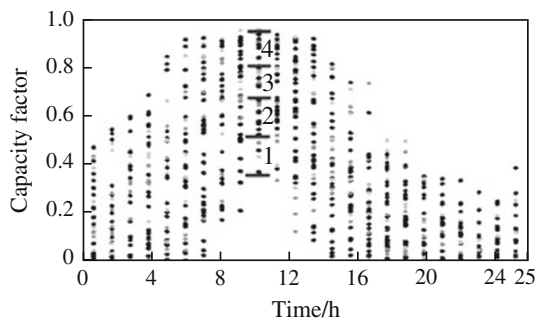


Fig. 1 Four-state wind power in pattern r_w

where $P_{i,j_m}(t)$ and $p_{i,j_m}^m(t)$ are the available power of conventional generator i in state j_m and the corresponding probability at sub-period t for given probability distribution of initial states p_0 . The total state number of the generator i is k_m . Four-state Markov model is used for the units. Considering that a unit has four states 1, 2, 3, and 4 with corresponding performance level $P_1 = 0$, $P_4 = P_{nom}$ and the values of P_2, P_3 can be obtained by the apportioning method [13], $p_{j_m}(t)$ is a probability and the process is in state j_m at time instant $t \geq 0$. The transition intensity matrix $A_{m_i}^m = (a_{j_m q_m})$ ($j_m, q_m = 1, 2, \dots, 4$) can be obtained as the following polynomial [14]:

$$T_{\sum j_m} = \sum_{m=1}^{k_{j_m}} T_{j_m}^{(m)} \quad (10)$$

$$a_{j_m q_m} = \frac{k_{j_m q_m}}{T_{\sum j_m}}, \quad j_m \neq q_m \quad (11)$$

$$a_{j_m j_m} = - \sum_{\substack{q_m=1 \\ q_m \neq j_m}}^N a_{j_m q_m} + 1 \quad (12)$$

where k_{j_m} is the accumulated number of the unit residence in state j_m during observation period T , $T_{j_m}^{(m)}$ is the time of the m -th unit residence in state j_m during observation period T , $T_{\sum j_m}$ is the accumulated time of the system residence in each state j_m during observation period T , $k_{j_m q_m}$ is the accumulated number of the unit transition from state j_m to state q_m during observation period T .

With the differential equations in [14], state-probabilities $p_{j_m}(t)$ can be obtained under given initial conditions. Therefore, dynamic reliability measures for generating units can also be obtained.

3.3 Reliability model for load model

The historical data of load, such as wind power data, are handled by using a hierarchical clustering algorithm and principal component feature extraction technology. The UGF model of load i in pattern r_L at sub-period t is described as follows:

$$u_i^L(z, t) = \sum_{j_L=1}^{k_L} p_{i,j_L}^L(t) z^{D_{i,j_L}(t)} \quad (13)$$

where $D_{i,j_L}(t)$ and $p_{i,j_L}^L(t)$ are the load capacity and probability, respectively, k_L is the total state number of loads.

3.4 System UGF considering transmission network

System UGF combines UGFs of all power system components, including UGF of transmission network



which is formulated as system states. For a N -bus system with k_n system states, the system UGF can be obtained by the optimal power flow operator $\Omega_{\Phi OPF}$:

$$\begin{aligned}
 u^s(z, t) &= \Omega_{\Phi OPF} \{u_i^L(z, t), u_i^W(z, t), u_i^m(z, t)\} \\
 &= \sum_{i=1}^N \sum_{j_L=1}^{k_L} \sum_{j_w=1}^{k_w} \sum_{j_m=1}^{k_m} \sum_{j_n=1}^{k_n} p_{i,j_L}^L(t) \cdot p_{i,j_w}^W(t) \\
 &\quad \cdot p_{i,j_m}^m(t) \cdot p_{j_n}^T(t) \\
 &\quad \cdot z^{\Phi OPF \{D_{i,j_L}(t), WP_{i,j_w}(t), P_{i,j_m}(t)\}} \\
 &= \sum_{j_s=1}^{K_s} p_{j_s}^s(t) z^{LC_{j_s}(t)} \tag{14}
 \end{aligned}$$

where $p_{j_s}^s(t)$ and $LC_{j_s}(t)$ are the probability and load curtailment of system state j_s , respectively, $p_{j_n}^T(t)$ is the probability for the transmission network state j_n , K_s is the total state number including all state combination.

4 Probabilistic production simulation

On the basis of the probabilistic production simulation method [17], and the improved UGF techniques, considering the minimum outage time constraints and peak-shaving constraints of generator, a UGF model can be established. During the probabilistic production simulation of power systems, wind power, thermal generator and peak-shaving units are dispatched. In UGF, conventional units are divided into several levels of output, which have different generating costs per MWh according to base load (minimum output part) and peak load (adjustable output part) for load dispatching.

After simulation, we can obtain the reliability index loss of load probability $L_{LOLP}, r(t)$ and Expected Energy Not Supplied $E_{EENS}, r(t)$ in each composite pattern r_s at sub-period t :

$$L_{LOLP}, r_s(t) = 1 - p_{j_s}^s |_{LC_{j_s}(t)=0}(t) \tag{15}$$

$$E_{EENS}, r_s(t) = \sum_{j_s=1}^{K_s} p_{j_s}^s(t) LC_{j_s}(t) \tag{16}$$

The MSS system reliability indices at sub-period t can be calculated as

$$\begin{cases}
 L_{LOLP}(t) = \sum_{s_i=1}^{R_s} \alpha_{s_i} L_{LOLP}, s_i(t) \\
 E_{EENS}(t) = \sum_{s_i=1}^{R_s} \alpha_{s_i} E_{EENS}, s_i(t) \\
 R_s = \prod_{i=1}^N \prod_{L=1}^{R_L} \prod_{w=1}^{R_W} r_{i,L} r_{i,w} \\
 \alpha_{s_i} = \prod_{i=1}^N \alpha_{i,L} \alpha_{i,w}
 \end{cases} \tag{17}$$

where R_s, R_L, R_W are total numbers of the combination of system pattern, the load pattern and the wind farm output pattern, respectively; $\alpha_{s_i}, \alpha_{i,L}, \alpha_{i,w}$ are the probabilities of system pattern r_{s_i} , the pattern of the i -th load $r_{i,L}$, and the wind power output pattern of the i -th wind farm $r_{i,w}$, respectively.

We can obtain reliability indices, such as Loss of Load Expectation L_{LOLE} and Expected Energy Not Supplied E_{EENS} over different periods through accumulation based on the dynamic probability distribution of the conventional generators and different patterns of wind farm or loads:

$$\begin{cases}
 L_{LOLE} = \sum_{t=1}^T L_{LOLP}(t) T' \\
 E_{EENS} = \sum_{t=1}^T E_{EENS}(t)
 \end{cases} \tag{18}$$

where T' is the number of hours for each sub-period, and $T' = 1$ in this paper, T is the total number of sub-periods for reliability assessment.

5 Case study

The IEEE-RTS has been modified to illustrate the proposed models and techniques: original data can be found elsewhere [18]. Table 1 shows the minimum output of different types of units.

The IEEE-RTS load is a scaled-down version of load shape from the power grid of Shandong province with a 2,850 MW peak load. The load data of the test system are constructed by using the load data of power grid of Shandong province in 2009 with a 39,025 MW peak load and the scaling factor of 2,850/39,025. The study period is one year. We make use of the several years' historical hourly wind speed data of Zhangbei wind farm in North China with a total wind capacity of 680 MW.

5.1 Clustering of wind power and UGF model

To balance efficiency and accuracy, choosing a suitable number of clusters is important. Guidelines on choosing a

Table 1 Minimum output of conventional units

Generation type	Minimum output (MW)	Generation type	Minimum output (MW)
U12	0.0	U155	86.8
U20	0.0	U197	0.0
U50	0.0	U350	192.5
U76	41.0	U400	400.0
U100	0.0		

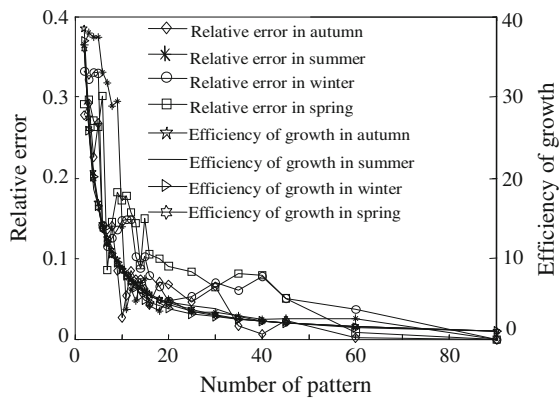


Fig. 2 Relationship between the number of clusters and the relative errors or growth efficiency

Table 2 Probability of each pattern

Season	Probability (%)				Pattern coverage rate (%)
	Pattern 1	Pattern 2	Pattern 3	Pattern 4	
Spring	27.78	8.89	38.89	8.89	84.45
Summer	49.00	22.22	17.78	—	89.00
Autumn	33.33	30.00	16.67	—	80.00
Winter	26.67	42.22	21.11	—	90.00

suitable number of clusters are obtained based on statistical data in this case. Relative errors and growth efficiency are calculated over different seasons and the results are shown in Fig. 2.

Figure 2 indicates that the relationship between the number of clusters and the relative error is non-linear. The relationship between the number of clusters and the growth efficiency is non-linear. The expected number of the clusters would be found according to the inflexion value in the curve. Considering the relative error and growth efficiency, the number of clusters is chosen between 2% and 5% of the number of total research days, thus the number of clusters is 48 *per annum*.

Given space limitations, only the main modes with larger probabilities are listed. The centroid of each cluster and its corresponding probability are shown in Table 2 and Fig. 3.

As can be seen, the fluctuations and the corresponding probability of different clusters varied, the method can readily extract the salient and time-varying patterns of wind generation. Moreover, the characteristics varied seasonally: the low average power pattern has a larger probability of 49% in Summer, however, the high average power patterns has the larger probabilities of 42.22% and 38.89%, respectively in Winter and Spring, showing that the proposed method can extract the seasonal characteristics of wind power output.

Four to six states can reflect the characteristics of wind speed and load [19], so we can choose four-state models for wind farms in each sub-period by an apportioning method. Multi-state models of wind power output are only shown in sub-periods 4 to 8, and 16 to 20 of the pattern 2 in Summer in Table 3 due to space limitations.

As can be seen, the value and the probability of wind power output in different sub-periods varied, hence, the

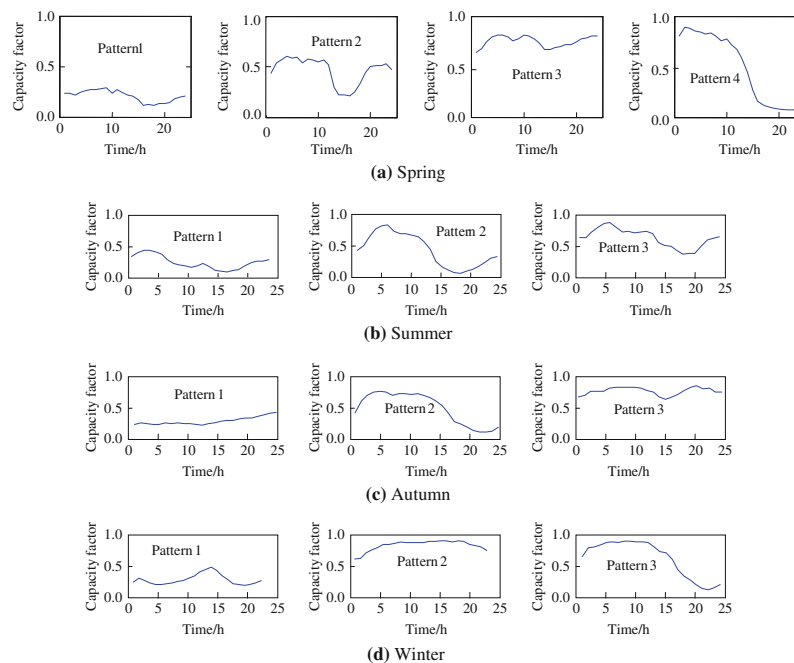


Fig. 3 Centroids of wind power patterns in a year



Table 3 Wind power (WP) and probability (p) in UGF model

Period	WP (MW)	WP/ Δc	p	Period	WP (MW)	WP/ Δc	p
4	120	12	0.111	16	80	8	0.296
	264	26	0.148		211	21	0.222
	409	41	0.296		342	34	0.296
	553	55	0.444		472	47	0.185
5	181	18	0.111	17	57	6	0.296
	302	30	0.148		168	17	0.296
	422	42	0.296		279	28	0.148
	542	54	0.444		390	39	0.259
6	285	28	0.222	18	61	6	0.370
	372	37	0.148		173	17	0.259
	458	46	0.259		285	29	0.185
	545	55	0.370		397	40	0.185
7	269	27	0.333	19	69	7	0.407
	360	36	0.074		176	18	0.296
	451	45	0.296		283	28	0.222
	543	54	0.259		390	39	0.074
8	225	23	0.185	20	60	6	0.518
	339	34	0.222		179	18	0.296
	454	45	0.333		298	30	0.111
	568	57	0.259		417	42	0.074

Table 4 Observed numbers $k_{j_m q_m}$ of the unit transiting from state j_m to state q_m , generating capacity P_{j_m} and residence accumulated time $T_{\sum j_m}$ in state j_m

State number	1	2	3	4	Generating capacity P_{j_m} (MW)	Accumulated time $T_{\sum j_m}$ (h)
1	–	6	1	0	0	75
2	1	–	11	1	117	34
3	0	3	–	37	233	104
4	6	4	28	–	350	40,711

traditional UGF method is crude. The time varying UGF can reflect the sequential volatility of wind power output. The common capacity factor $\Delta c = 10$ MW, all of the state values are expressed as integer multiples of Δc , and the number of states combination of MSS are prevented from growing exponentially.

5.2 Time dependent state probability of the conventional generator

A typical real coal-fired generating unit U350 is observed over 5 years [14]. The observed numbers $k_{j_m q_m}$ of the unit transition from state j_m to state q_m are presented in Table 4. The generator expectation output P_{j_m} and residence accumulated time $T_{\sum j_m}$ for each state j_m are also shown.

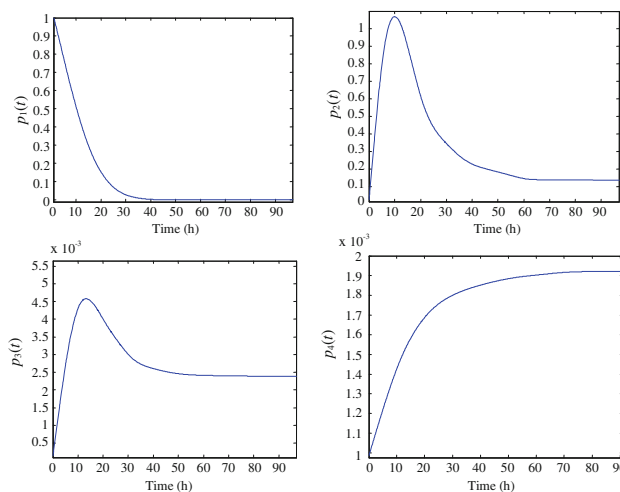


Fig. 4 Time dependent state probability of U350

Table 5 Simulation results: seasonal variations

Season	L_{LOLE} (h/a)	E_{EENS} (MWh)	Fuel cost ($\times 10^7$ USD)	CO ₂ emissions ($\times 10^5$ ton)
Spring	0.28	2.5489	1.3767	3.9966
Summer	1.86	199.65	2.9598	5.1262
Autumn	0.55	35.959	2.1897	4.8230
Winter	1.14	109.64	2.4521	4.9956
Year	3.83	347.7979	8.9783	18.9414

By using (10) to (12), the following matrix of point estimations of transition intensities is computed:

$$|a_{j_m q_m}| = \begin{vmatrix} 0.9067 & 0.0800 & 0.0133 & 0 \\ 0.0294 & 0.6177 & 0.3235 & 0.0294 \\ 0 & 0.0288 & 0.6154 & 0.3558 \\ 0.0002 & 0.0001 & 0.00070 & 0.999 \end{vmatrix} \quad (19)$$

Each $a_{j_m q_m}$ in (19) is represented by such units as 1/h.

Therefore, we can obtain the time dependent state probability of the typical conventional generator U350 with Lz -transform. The state probabilities are changed with time in initial state, as shown in Fig. 4.

From these figures, it is observed that the state probability of U350 is time-varying, and the difference is great enough, therefore the unit steady-state (long-term) reliability cannot characterize the transient (short-term) reliability.

5.3 Probabilistic production simulation: seasonal variations

We divided the wind power data into four classes according to season, and then acquired the wind power pattern in each season. The results are shown in Table 5.

Table 6 Simulation results: Summer patterns

Load	Wind power output (%)	E_{EENS} (MWh)	Fuel costs (1×10^5 USD)	CO ₂ emissions (kton)
L1 Workday (5/7)	49 (R1)	0.1523	1.2936	4.3693
	22.22 (R2)	0.0556	1.0500	3.8962
	17.78 (R3)	0.0321	0.9165	3.3216
L2 Weekday (2/7)	49 (R1)	0.3578	0.6521	2.5901
	22.22 (R2)	0.3488	0.5168	2.1102
	17.78 (R3)	0.0135	0.4001	1.6809

Note: L1 denotes load pattern 1, L2 denotes load pattern 2; R1, R2, and R3 are wind power output patterns 1, 2, and 3, respectively

We can see that the reliability indices in different seasons varied. The reliability index in spring is the lowest, because the probability of high wind power patterns is larger and the load is lower. The reliability index in summer is the largest, because the probability of low wind power patterns is larger and the load is higher. In addition, fuel cost and CO₂ emissions in summer are larger, because the low wind power patterns widen the peaks and valleys of the equivalent system load, and need more peaking units. The method can reflect the correlation of wind power and load: this correlation is seasonal.

5.4 Probabilistic production simulation considering wind power and load pattern

Take summer as an example: the time-varying wind power pattern is shown in Fig. 3, and then the UGF model for time-varying wind power output is established. The workday pattern and weekday pattern of load according to the weekly load characteristics are acquired, and the probabilistic production simulation is done and the simulation results, such as the reliability index, fuel costs, and CO₂ emissions are shown in Table 6.

In the same load pattern, the reliability index is different for different wind power patterns. Furthermore, in the same wind power pattern, the reliability index, fuel cost, and CO₂ emissions vary with different load patterns due to the differences in the correction between wind power and load. In a further illustration, the impact of wind power on power systems is not only related to the wind power pattern itself, but also the correction between the wind power and the load.

6 Conclusions

An improved universal generating function based on probabilistic production simulation with wind power penetration is proposed. Meanwhile, by clustering the wind

power data from the Zhangbei wind power farm in North of China, the IEEE-RTS is modified to test the probabilistic production simulation. The conclusions are summarised as follows:

- 1) The salient, time-varying pattern of wind power has been extracted by feature extraction and cluster technology.
- 2) A sequential UGF model is established for conventional generators with discrete-states continuous-time Markov process. By using the model, reliability indices can be more accuracy by considering specific load and wind farm output patterns of system.
- 3) The improved UGF method can effectively calculate the system reliability over different time and specific wind power output patterns.
- 4) The proposed approach explicitly quantifies the impact of the temporal correlation between wind power and system load on reliability indices, fuel cost, and CO₂ emissions.

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