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Short-Term Reliability Assessment of Generating Systems Considering Demand Response Reliability

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ABSTRACT Demand response (DR), one kind of flexible resources, can decrease the operating costs of power systems and improve their reliability. However, DR is not absolutely reliable due to its inherent uncertainty, so its function of improving system reliability is restricted. In order to estimate the risk of generating systems during the period of DR events, the short-term reliability assessment of generating systems considering DR reliability is studied in this paper. Firstly, a multi-state continuous-time Markov chain (CTMC) model of DR response capacity is established and the state division of response capacity is performed by the method of mean-standard deviation (MSD) classification. Secondly, the transition matrix of DR response capacity is estimated according to the sequence of DR response capacity. Thirdly, the CTMCs of demand response providers' (DRP) response capacity and those of generating units' (GU) output capacity are converted into universal generating functions (UGF) by *Lz*-transform. Finally, the transient distribution of DR response capacity and GU output capacity are derived, and the short-term reliability assessment method for generating systems considering DR reliability is proposed. A case study on a revised IEEE-RTS79 system shows the application of the presented method. The method proposed in this paper can assist system operators to evaluate the reliability of generating systems during the period of DR events.

INDEX TERMS Demand response reliability, Markov chain, mean-standard deviation classification, short-term reliability assessment of generating systems, universal generating function.

I. INTRODUCTION

To improve energy utilization efficiency and defer costly investments on power generation, a flexible and effective measure known as demand side management (DSM) has received considerable attention over the past four decades and been applied to the power systems of many countries. In recent years, to develop smart grids [1]–[3] accommodating more renewable energy resources, researchers have shown an increased interest in demand response (DR), an important solution to DSM.

According to the definition from the U.S. Department of Energy (DoE), DR is changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized [4]. By adjusting demand instead of supply, DR can help curtail peak load and keep the balance between generation and demand, decreasing system operating costs and increasing the reliability of power systems [5]–[7]. However, compared with traditional resources such as generators, transmission lines, and storage devices, loads are highly uncertain [8], which will necessarily restrict the role of DR.

Therefore, uncertainty of DR has attracted considerable scholarly attention recently. Some research has been carried out on DR uncertainty [9], [10], while other research has mainly focused on the impact of DR uncertainty on power systems: some academic literature addresses the optimal scheduling and operation of power systems with uncertain DR, such as unit commitment [11], [12], economic

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dispatch [13], and optimal reserve market clearing [14]; some pays particular attention to the impact of DR uncertainty on renewable energy accommodation [15]–[18]; some discusses the market mechanism design for DR uncertainty [19]–[21]; and a little has been concerned with the planning of power systems considering DR uncertainty [22].

Apart from the above, it is equally necessary to take the uncertainty of DR into account when studying the role of DR in improving the reliability of power systems. However, most of previous studies [23]–[28] have generally ignored the uncertainty of DR, i.e. assumed that DR will never fail to respond during the period of DR events. Surely some studies [29]–[32] have considered the uncertainty of DR: a probabilistic framework for optimal DR scheduling in the day-ahead planning of transmission networks is proposed in [29], and the results show that the proposed DR scheduling improves both reliability and economic indices; a new framework for congestion management utilizing a reliability model of DR resources is proposed in [30] and the multi-state model of DR resources considering repairable advanced metering infrastructures is also presented; a framework for reliability assessment and risk implications of post-fault DR in smart distribution networks is presented in [31]; a reliability model of the demand resource is developed to represent the customer behavior, and the reliability indices of power systems are calculated in [32]. Nevertheless, the literature above only addresses the steady reliability model of DR and the long-term steady reliability assessment of power systems. In fact, power system operators are more interested in the short-term reliability of power systems during the period of DR events, which relates to the transient distribution of DR response capacity.

Short-term reliability assessment [33]–[38] plays an important role in operating reserve planning, operating reliability prediction and adaptive security control of power systems. And multi-state Markov models, universal generating functions (UGF) and *Lz*-transforms are the essential tools to perform short-term reliability assessment. Firstly, multi-state Markov models apply to the reliability modelling of equipment such as coal fired power generators [34], [35], rapid start-up generators and wind farms [36], and thermostatically-controlled-loads [37]. Furthermore, UGFs and *Lz*-transforms [35]–[38] are appropriate for dealing with complex multi-state systems: the *Lz*-transform method is applied to short-term reliability evaluation of power stations in [35], decreasing drastically a computation burden; UGFs are used to establish the time-varying reliability models of wind farms, conventional generators and rapid start-up generators in [36]; the multi-state reliability model of operating reserve provided by thermostatically-controlled-loads is represented by the *Lz*-transform approach in [37]; and in [38], UGFs are used to represent the capacity distribution of generators and the demand distribution of nodes. Despite those recent findings about the mechanism of short-term reliability, there is a lack of short-term reliability modelling of DR, which includes the state division of DR response capacity and the estimation of transient distribution, making it difficult to evaluate the operating risk of generating systems during the period of DR events.

Therefore, in order to evaluate the short-term reliability of generating systems during the period of DR events, the time-varying transient reliability model should be established firstly, including the state division of DR response capacity and the transient distribution of DR response capacity. The main contributions of the paper exit in: (i) DR response capacity is classified into several states by the method of mean-standard deviation (MSD) classification and it is modelled as a continuous-time Markov chain (CTMC); (ii) The time-varying transient distribution of DR response capacity and generating unit (GU) output capacity, which is suitable for short-term reliability assessment through computers, is deduced; (iii) The algorithm based on UGFs for the short-term reliability assessment of generating systems considering DR reliability is proposed to calculate the time-varying and the average reliability indices, which can be used to analyze the risk of generating systems during periods of DR events.

The framework of research work in this paper is illustrated in Fig. 1. Note that the CTMC modelling of GU output capacity is not discussed in detail in the paper because it can be found in existing references. And the remainder of this paper is organized as follows. The short-term reliability model of DR response capacity, represented by a multi-state CTMC, is established in Section II. The state division of DR response capacity and the estimation of its transition matrix are discussed in Section III. Then in Section IV, the CTMCs of both DR response capacity and GU output capacity are converted into UGFs by *Lz*-transform; and then the total response capacity of all demand response providers (DRP) and the total output capacity of all GUs are represented by UGFs. In Section V, the transient distribution of DR response capacity and GU output capacity are derived, and the algorithm for the short-term reliability assessment of generating systems considering DR reliability model is presented. A case study on a revised IEEE-RTS79 system illustrates the application of the approach in Section VI. Finally, the conclusion and future work are summarized in Section VII.

II. SHORT-TERM RELIABILITY MODELS FOR DR AND GUs

A. CONTINUOUS-TIME MARKOV CHAIN

Consider a CTMC, $X(t) \in \{x_1, x_2, \cdots, x_N\}$, shown in Fig. 2, and it has N states. The performance level associated with any state i is denoted as x_i $(i = 1, 2, \cdots, N)$. λ_{ij} is the transition rate from state i to state j, where i and j belong to the set $\{1, 2, \ldots, N\}$.

Transition matrix denoted by $\mathbf{Q}$ is represented in

$$\mathbf{Q} = \begin{pmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1N} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{N1} & \lambda_{N2} & \cdots & \lambda_{NN} \end{pmatrix} \tag{1}$$

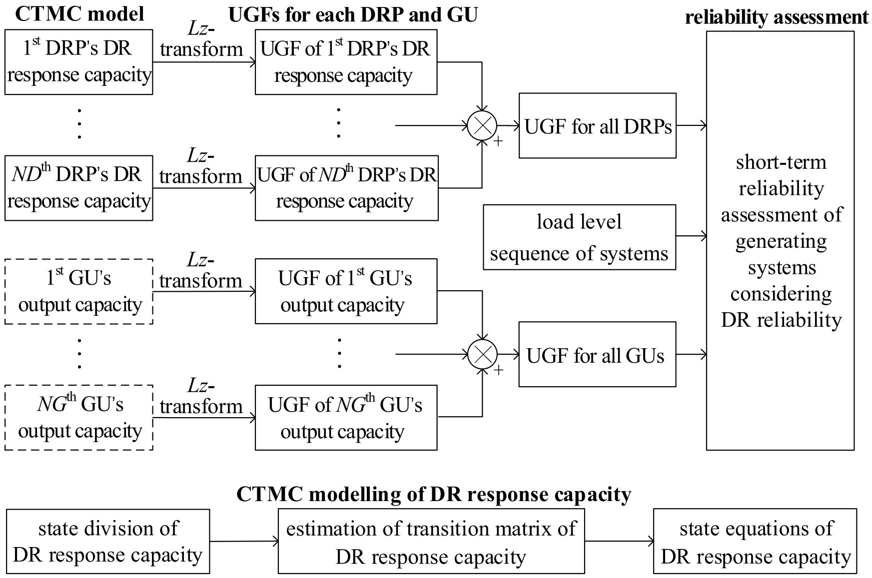

FIGURE 1. Framework of research work in this paper. Note that ND and NG are the numbers of DRPs and GUs, respectively, and $\otimes_+$ is the combination operator of addition.

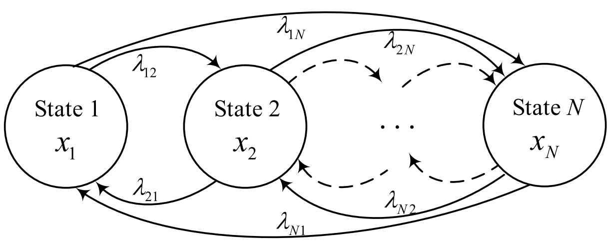

FIGURE 2. ***N*-state CTMC model. N is the number of states. x_i is the performance level in state *i* and λ_{ij} is the transition rate from state *i* to state *j*, where *i* and *j* belong to $\{1, 2, \ldots, N\}$.**

where the diagonal elements λ_{ii} satisfy

$$\lambda_{ii} = -\sum_{\substack{j=1 \\ j\neq i}}^{N} \lambda_{ij} \left(i \in \{1, 2, \cdots N\}\right) \tag{2}$$

Designate $p_i(t)\,(i = 1, 2, \cdots, N)$ as the probability of $X(t)$ staying in state i at moment $t\,(t \geq 0)$; and denote the transient distribution of $X(t)$ as $\mathbf{p}(t)$, which is the row vector consisting of $p_i(t)\,(i = 1, 2, \cdots, N)$.Then the state equations can be expressed in:

$$\frac{d}{dt}\mathbf{p}(t) = \mathbf{p}(t) \cdot \mathbf{Q} \tag{3}$$

In addition, the stationary distribution of $X(t)$, denoted by $\mathbf{p}^{\infty} = \left(p_1^{\infty}, p_2^{\infty}, \ldots, p_N^{\infty}\right)$, can be obtained through

$$\begin{cases} \mathbf{p}^{\infty} \cdot \mathbf{Q} = \mathbf{0} \\ \sum_{i=1}^{N} p_i^{\infty} = 1 \end{cases} \tag{4}$$

In short-term reliability assessments, we should use $\mathbf{p}(t)$ rather than $\mathbf{p}^{\infty}$ which is only suitable for long-term (or steady-state) reliability assessments.

B. SHORT-TERM RELIABILITY MODEL OF DR RESPONSE CAPACITY AND GU OUTPUT CAPACITY

DR is influenced by some stochastic factors such as the unexpected behavior of customers and the changeable weather, so the response capacity of DR is full of uncertainties, affecting the reliability of power systems. In order to analyze the uncertainty of DR, the above-mentioned CTMC well-known in the field of reliability analysis is applied to establish the short-term reliability model of DR response capacity. The process to establish the short-term reliability model of DR response capacity consists of the following steps: dividing the response capacity of DR into several states, estimating the transition matrix and establishing the state equations of DR response capacity, which will be discussed in Section III.

Similarly, the output capacity of a GU is stochastic, varying from zero to its nominal generating capacity. The process to establish the short-term reliability model of GU output capacity is the same as DR response capacity except the estimation of transition rates which can be found in other references such as [34]. And this paper makes the stress on DR reliability and its effect on the short-term reliability of generating systems. Therefore, the estimation of transition rates of GU output capacity is not discussed in the paper and in case study the transition rates of GU output capacity use the values in the IEEE test system.

III. PARAMETER ESTIMATION IN CTMC MODEL OF DR RESPONSE CAPACITY

A. SEQUENCE OF DR RESPONSE CAPACITY

The customer's load curve without implementing DR, represented by $L_1(t)$, can be obtained through load forecasts; and the load curve when implementing DR, represented by $L_2(t)$, can be available through measurements. Suppose that

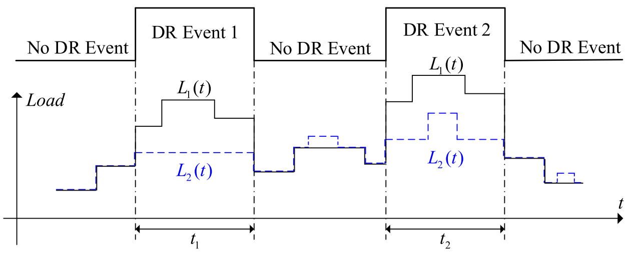

FIGURE 3. DR events and load curves. The solid lines represent the load curve without DR's participation; and the dotted lines represent the measured load curve when DR is executed.

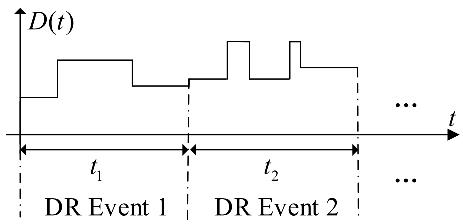

FIGURE 4. Sequence of DR response capacity during the period of DR events.

the sampling intervals of these two load curves are the same, which maybe 10, 15, 20, or 60 minutes. Fig. 3 displays the load curves of a customer, where the rising edge and the falling edge represent the start and the end of a DR event, respectively. The solid lines represent the load curve without DR's participation; and the dotted lines represent the measured load curve when DR is executed. Reduced loads during periods of DR events are defined as the response capacity; and increased loads during periods of no DR events are caused by the shifted loads from periods of DR events, or DR rebounds. In the paper, we are mainly concerned with the reliability of generating systems during the period of DR events so the DR response capacity during DR events, denoted by $D(t)$, can be obtained according to

$$D(t)=L_1(t)-L_2(t),\ t \text{ belongs to periods of DR events} \quad (5)$$

All the DR events are put together to get the sequence of DR response capacity during DR events, shown in Fig. 4. The parameters of the multi-state CTMC model of DR response capacity can thus be estimated through the statistical analysis of this sequence.

B. STATE DIVISION OF DR RESPONSE CAPACITY

To apply the multi-state CTMC model mentioned above, it is essential to classify DR response capacity into several states firstly. The commonly-used methods of state division include the mean-standard deviation (MSD) classification, the clustering classification, and the optimal segmentation. In this paper, the MSD classification is adopted.

TABLE 1. State division of DR response capacity when N_D is an odd number.

State, i	Interval, E_i
1	$[D_{\min}, \bar{D}-(N_D-1)S/4)$
2	$[\bar{D}-(N_D-1)S/4, \bar{D}-(N_D-3)S/4)$
……	……
$(N_D+1)/2-1$	$[\bar{D}-S, \bar{D}-0.5S)$
$(N_D+1)/2$	$[\bar{D}-0.5S, \bar{D}+0.5S)$
$(N_D+1)/2+1$	$[\bar{D}+0.5S, \bar{D}+S)$
……	……
N_D-1	$[\bar{D}+(N_D-3)S/4, \bar{D}+(N_D-1)S/4)$
N_D	$[\bar{D}+(N_D-1)S/4, D_{\max}]$

TABLE 2. State division of DR response capacity when N_D is an even number.

State, i	Interval, E_i
1	$[D_{\min}, \bar{D}-(N_D-2)S/4)$
2	$[\bar{D}-(N_D-2)S/4, \bar{D}-(N_D-4)S/4)$
……	……
$N_D/2$	$[\bar{D}-0.5S, \bar{D})$
$N_D/2+1$	$[\bar{D}, \bar{D}+0.5S)$
……	……
N_D-1	$[\bar{D}+(N_D-4)S/4, \bar{D}+(N_D-2)S/4)$
N_D	$[\bar{D}+(N_D-2)S/4, D_{\max}]$

According to the sequence of DR response capacity, its mean and standard deviation can be obtained through

$$\bar{D} = \frac{1}{K}\sum_{k=1}^{K} D(k) \quad (6)$$

$$S = \sqrt{\frac{1}{K-1}\sum_{k=1}^{K}\left(D(k)-\bar{D}\right)^2} \quad (7)$$

where $\bar{D}$ and S are the mean value and the standard deviation of the sequence of DR response capacity, respectively; K is the size of this sequence. According to the central limit theorem, DR response capacity can be divided into N_D groups. If N_D is an odd number, the state space of DR response capacity can be partitioned according to Table 1; otherwise it can be partitioned according to Table 2. In both tables, E_i is the interval of DR response capacity in the ith state; $D_{\min}$ and D_{max} are the minimum and the maximum values of the sequence of DR response, respectively.

Then the performance level of DR response capacity in each state, denoted by $\bar{D}_i \left(i = 1, 2, \cdots, N_D\right)$, is calculated out by

$$\bar{D}_i = \mathrm{mean}(D(k)), \quad D(k) \in E_i \tag{8}$$

where the function 'mean' represents the operation of arithmetic mean.

C. ESTIMATION OF TRANSITION MATRIX OF DR RESPONSE CAPACITY

The transition rate of DR response capacity from state$i$ to j can be calculated out by

$$\lambda_{ij}^{\mathrm{D}} = \frac{f_{ij}}{T_i} \, (i, j \in \{1, 2, \cdots N_{\mathrm{D}}\}, i \neq j) \tag{9}$$

where $\lambda_{ij}^{\mathrm{D}}$ is the transition rate from state$i$to j, and the superscript D indicates DR; T_i is the total residence time when DR response capacity is in state i; f_{ij} is the number of transitions from state$i$ to j during the period of time T_i.

Then the transition matrix of DR response capacity, denoted by $\mathbf{Q}_{\mathrm{D}}$, can be obtained by

$$\mathbf{Q}_{\mathrm{D}} = \begin{pmatrix} \lambda_{11}^{\mathrm{D}} & \lambda_{12}^{\mathrm{D}} & \cdots & \lambda_{1N_{\mathrm{D}}}^{\mathrm{D}} \\ \lambda_{21}^{\mathrm{D}} & \lambda_{22}^{\mathrm{D}} & \cdots & \lambda_{2N_{\mathrm{D}}}^{\mathrm{D}} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{N_{\mathrm{D}}1}^{\mathrm{D}} & \lambda_{N_{\mathrm{D}}2}^{\mathrm{D}} & \cdots & \lambda_{N_{\mathrm{D}}N_{\mathrm{D}}}^{\mathrm{D}} \end{pmatrix} \tag{10}$$

where the diagonal elements $\lambda_{ii}^{\mathrm{D}}$ can be obtained by

$$\lambda_{ii}^{\mathrm{D}} = -\sum_{\substack{j=1 \\ j \neq i}}^{N_{\mathrm{D}}} \lambda_{ij}^{\mathrm{D}} \, (i \in \{1, 2, \cdots N_{\mathrm{D}}\}) \tag{11}$$

Furthermore, state equations of DR response capacity can be expressed in terms of the following differential equations

$$\frac{d}{dt}\mathbf{p}_{\mathbf{D}}(t) = \mathbf{p}_{\mathbf{D}}(t) \cdot \mathbf{Q}_{\mathrm{D}} \tag{12}$$

where $\mathbf{p}_D(t)$ is the transient distribution of DR response capacity at moment t. Given the initial distribution $\mathbf{p}_D(t_0)$ at moment t_0, the transient distribution $\mathbf{p}_D(t)$ will be obtained by solving the above differential equations.

IV. LZ-TRANSFORM OF DRPs' RESPONSE CAPACITY AND GUs' OUTPUT CAPACITY

The Lz-transform of a CTMC can transform the CTMC into the form of UGFs which have been proved to effectively represent multi-state systems. Hence, in the paper, the response capacity of DRPs and the output capacity of GUs are represented by UGFs through Lz-transform.

A. LZ-TRANSFORM AND UGFs

Taking the CTMC, $X(t) \in \{x_1, x_2, \cdots, x_N\}$, mentioned in section II, as an example, the Lz-transform of $X(t)$ is defined as follows

$$Lz\{X(t)\} = u_X(z, t) = \sum_{i=1}^{N} p_i(t) z^{x_i} \tag{13}$$

where z in general is a complex variable; $u_X(z, t)$ is the result of the Lz-transform, known as the UGF of the CTMC $X(t)$. The mathematical expectation of $X(t)$ at moment t, i.e.$E(X(t))$, can be obtained through

$$E(X(t)) = u'_X(z = 1, t) \tag{14}$$

where u'_X represents the first-order derivative of the UGF $u_X(z, t)$ with respect to z.

Assume that there are mutually independent H CTMCs, denoted by$X_1(t), X_2(t), \cdots, X_H(t)$, and that the process $X_i(t)\,(i = 1, 2, \cdots, H)$ has N_i possible states where the performance level associated with any state j is $x_{ij}\,(j = 1, 2, \cdots, N_i)$. If another stochastic process $Y(t)$ is the function of $X_i(t)$, i.e. $Y(t) = f\big(X_1(t), X_2(t), \cdots, X_H(t)\big)$, the Lz-transform of $Y(t)$ can be represented by

$$\begin{aligned} Lz\{Y(t)\} &= u_Y(z, t) \\ &= \otimes_f(u_{X_1}(z), u_{X_2}(z), \cdots, u_{X_H}(z)) \\ &= \sum_{j_1=1}^{N_1}\sum_{j_2=1}^{N_2}\cdots\sum_{j_H=1}^{N_H}\Big(\prod_{i=1}^{H} p_{ij_i}(t) z^{f(x_{ij_1}, \cdots, x_{ij_H})}\Big) \end{aligned} \tag{15}$$

where $\otimes_f$ is the combination operator of the function f and possesses both commutative and associative properties [39].

B. UGFs OF RESPONSE CAPACITY OF DRPs

DRPs include such DR providers as business customers, industrial customers, load aggregators and so on, who are willing to participate in DR programs. The response capacity of each DRP during the period of DR events is modelled as a CTMC which can be transformed into a UGF through Lz-transform. Then total response capacity of all DRPs is the sum of response capacity of each DRP. Each DRP generally owns the DR resources not shared with others, so the state of one DRP's response capacity does not influence and is not influenced by the state of response capacity of the other(s). Therefore, we assume that the response capacity of each DRP is mutually independent and the total response capacity of DRPs can also be represented by a UGF through the combination operator of addition.

Suppose there are ND DRPs in a generating system, and the response capacity of DRP $i\,(i = 1, 2, \cdots, ND)$, denoted as $D_i(t)$, is represented by a UGF shown in

$$u_{D_i}(z, t) = \sum_{j=1}^{N_{\mathrm{D}_i}} p_{\mathrm{D}ij}(t) z^{d_{ij}} \tag{16}$$

where $N_{\mathrm{D}i}$ is the state number of the response capacity of DRP i; $d_{ij}\,(j = 1, 2, \cdots, N_{\mathrm{D}i})$ is the performance level of the response capacity of DRP i; $p_{\mathrm{D}ij}(t)$ is the probability that the response capacity of DRP i at moment t is right in the state $j\,(j = 1, 2, \cdots, N_{\mathrm{D}i})$.

Total response capacity of DRPs, $D_s(t)$, is the sum of response capacity of each DRP, shown as

$$D_s(t) = \sum_{i=1}^{ND} D_i(t) \tag{17}$$

Then the UGF of $D_s(t)$ can be obtained by

$$u_{D_s}(z,t) = \otimes_+(u_{D_1}(z,t), u_{D_2}(z,t), \cdots, u_{D_{ND}}(z,t)) = \sum_{j_1=1}^{N_{D1}} \sum_{j_2=1}^{N_{D2}} \cdots \sum_{j_{ND}=1}^{N_{DND}} \left(\prod_{i=1}^{ND} p_{D_{ij_i}}(t) z^{d_{ij_1}+d_{ij_2}+\cdots+d_{ij_{ND}}}\right) \quad (18)$$

where $\otimes_+$ is the combination operator of addition.

C. UGFs OF OUTPUT CAPACITY OF GUs

The output capacity of a GU can also be represented by a multi-state CTMC model. State transition rates of GU output capacity can be obtained through statistical inference, which can be found in existing literature. For example, based on field observation, a technique for the estimation of transition rates between the various generating capacity levels of a power generating unit is proposed in [34]. Therefore, we will not repeat it here.

The transition matrix of GU output capacity is denoted by $\mathbf{Q}_G$ and its elements are shown in

$$\mathbf{Q}_G = \begin{pmatrix} \lambda_{11}^G & \lambda_{12}^G & \cdots & \lambda_{1N_G}^G \\ \lambda_{21}^G & \lambda_{22}^G & \cdots & \lambda_{2N_G}^G \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{N_G1}^G & \lambda_{N_G2}^G & \cdots & \lambda_{N_GN_G}^G \end{pmatrix} \quad (19)$$

where N_G is the state number of GU output capacity; λ_{ij}^G is the transition rate from state$i$ to j, and the superscript G indicates GU.

The output capacity of each GU during the period of DR events is also modelled as a CTMC which can be transformed into a UGF through Lz-transform. And total output capacity of all GUs is the sum of output capacity of each GU. The state of one GU's response capacity does not influence and is not influenced by the state of output capacity of the other(s). Therefore, the output capacity of each GU is mutually independent and the total output capacity of all GUs can also be represented by a UGF through the combination operator of addition.

Suppose that there are NG GUs in a generating system, and the output capacity of GU i $(i = 1, 2, \cdots, NG)$, $G_i(t)$, is represented by a UGF shown in

$$u_{G_i}(z,t) = \sum_{j=1}^{N_{Gi}} p_{Gij}(t) z^{g_{ij}} \quad (20)$$

where N_{Gi} is the state number of the output capacity of GU i; g_{ij} $(j = 1, 2, \cdots, N_{Gi})$ is the performance level of the output capacity of GU i; $p_{Gij}(t)$ is the probability that the output capacity of the GU i at moment t is in the state j $(j = 1, 2, \cdots, N_{Gi})$.

Total output capacity of GUs, $G_s(t)$, is the sum of output capacity of each GU, shown as

$$G_s(t) = \sum_{i=1}^{NG} G_i(t) \quad (21)$$

Then the UGF of $G_s(t)$ can be obtained by

$$u_{G_s}(z,t) = \otimes_+(u_{G_1}(z,t), u_{G_2}(z,t), \cdots, u_{G_{NG}}(z,t)) = \sum_{j_1=1}^{N_{G1}} \sum_{j_2=1}^{N_{G2}} \cdots \sum_{j_{NG}=1}^{N_{GNG}} \left(\prod_{i=1}^{NG} p_{G_{ij_i}}(t) z^{g_{ij_1}+g_{ij_2}+\cdots+g_{ij_{NG}}}\right) \quad (22)$$

V. SHORT-TERM RELIABILITY ASSESSMENT OF GENERATING SYSTEMS CONSIDERING DR RELIABILITY

The CTMCs of both DR response capacity and GU output capacity are time-continuous, which cannot be processed directly by computer. Therefore, firstly they should be discretized in the time domain to get the transient distribution of both DR response capacity and GU output capacity at each time interval.

A. TRANSIENT DISTRIBUTION OF DR RESPONSE CAPACITY

Although the transient distribution of DR response capacity, $\mathbf{p}_D(t)$, can be obtained by using numerical methods to solve the differential equations shown as (12), it is difficult to calculate the transient distribution quickly when the state number of DR response capacity increases. To avoid solving directly the differential equations, we convert the transition matrix of DR response capability into a transition probability matrix, and then calculate the transient distribution of DR response by the transition probability matrix and the initial distribution.

According to [40], the transition probability matrix of DR response capacity during a sampling interval can be obtained by

$$\mathbf{P}_D(\Delta t) = Exp(\mathbf{Q}_D \cdot \Delta t) \quad (23)$$

where $\mathbf{P}_D(\Delta t)$ is the transition probability matrix of DR response capacity; Δt is the sampling interval, which is equal to the sampling interval of the load curve mentioned in section III; Exp is the matrix exponential function.

Then the transient distribution of DR response capacity can be obtained through

$$\mathbf{p}_D(t_k) = \mathbf{p}_D(t_0) \cdot \mathbf{P}_D^k(\Delta t) \quad (24)$$

where $\mathbf{p}_D(t_0)$ is the initial probability distribution of DR response capacity; $\mathbf{p}_D(t_k)$ is the probability distribution of DR response capacity at moment t_k $(t_k = t_0 + k \bullet \Delta t)$; $\mathbf{P}_D^k(\Delta t)$is the k power of $\mathbf{P}_D(\Delta t)$.

B. TRANSIENT DISTRIBUTION OF GU OUTPUT CAPACITY

Similarly, the transition probability matrix of GU output capacity during a sampling interval can be obtained by

$$\mathbf{P}_G(\Delta t) = \mathrm{Exp}(\mathbf{Q}_G \cdot \Delta t) \quad (25)$$

where $\mathbf{P}_G(\Delta t)$ is the transition probability matrix of GU output capacity.

Then the transient distribution of GU output capacity can be obtained through

$$\mathbf{p}_G(t_k) = \mathbf{p}_G(t_0) \cdot \mathbf{P}_G^k(\Delta t) \quad (26)$$

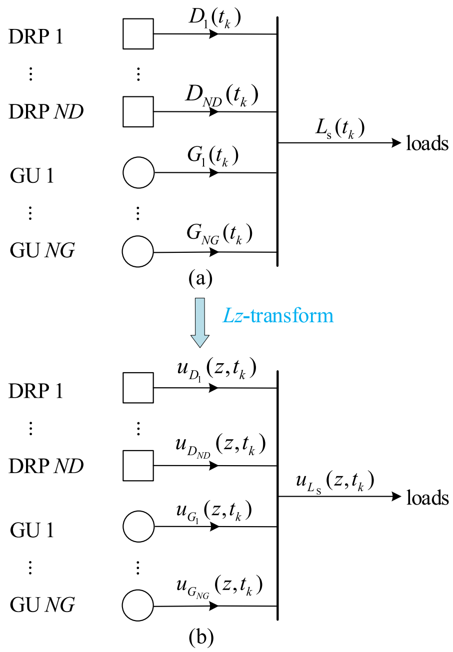

FIGURE 5. Generating system involving DRPs. (a) Generating system represented by stochastic processes, (b) Generating system represented by UGFs.

where $\mathbf{p}_{\mathrm{G}}(t_0)$ is the initial probability distribution of GU output capacity; $\mathbf{p}_{\mathrm{G}}(t_k)$ is the probability distribution of GU output capacity at moment t_k ($t_k = t_0 + k \bullet \Delta t$); $\mathbf{P}_{\mathrm{G}}^{k}(\Delta t)$ is the k power of $\mathbf{P}_{\mathrm{G}}(\Delta t)$.

C. SURPLUS CAPCITY AND RELIABILITY INDICES

A generating system involving DRPs is shown in Fig. 5. Equivalent generating capacity is defined as the sum of GUs' output capacity and DRPs' response capacity, and it should be greater than or equal to the load. Otherwise some loads will be curtailed to ensure the safe operation of the generating system.

Surplus capacity is the difference between the equivalent generating capacity and the system load, and it can be calculated by

$$S(t_k) = G_{\mathrm{s}}(t_k) + D_{\mathrm{s}}(t_k) - L_{\mathrm{s}}(t_k) \tag{27}$$

where $S(t_k)$ and $L_{\mathrm{s}}(t_k)$ are the surplus capacity and the load level of the system at moment t_k, respectively.

Note that both $G_{\mathrm{s}}(t_k)$ and $D_{\mathrm{s}}(t_k)$ are random variables, while $L_{\mathrm{s}}(t_k)$ is a deterministic value whose UGF, $u_{L_S}(z, t_k)$, can be represented by

$$u_{L_S}(z, t_k) = 1 \cdot z^{L_{\mathrm{s}}(t_k)} \tag{28}$$

Thus, the UGF of surplus capacity can be calculated by

$$u_S(z, t_k) = u_{G_s}(z, t_k) \otimes_+ u_{D_s}(z, t_k) \otimes_- u_{L_S}(z, t_k) \tag{29}$$

where $\otimes_-$ is the combination operator of subtraction.

The state and the curtailed load of a generating system can be determined by a loss of load index function (LLIF) and an unsupplied load function (ULF), respectively, which are collectively called as reliability test functions.

The LLIF is defined as

$$f_{\mathrm{l}}(S(t_k)) = \begin{cases} 1 & S(t_k) < 0 \\ 0 & S(t_k) \geq 0 \end{cases} \tag{30}$$

where f_{l} is the LLIF with binary values. If the surplus capacity is negative, the value of f_{l} is one, indicating the generating system is in failure states; otherwise, the value of f_{l} is zero, indicating it is in normal states.

And the ULF is defined as

$$f_{\mathrm{u}}(S(t_k)) = \max(-S(t_k), 0) \tag{31}$$

where f_{u} is the ULF. If the generating system is in failure states, the value of the ULF is $-S(t_k)$; otherwise, it is zero.

The UGFs of the LLIF and the ULF at moment t_k can be obtained according to the following equations.

$$u_{f_{\mathrm{l}}}(z, t_k) = \otimes_{f_{\mathrm{l}}} u_S(z, t_k) \tag{32}$$

$$u_{f_{\mathrm{u}}}(z, t_k) = \otimes_{f_{\mathrm{u}}} u_S(z, t_k) \tag{33}$$

where $u_{f_l}(z, t_k)$ and $u_{f_u}(z, t_k)$ are the UGFs of the LLIF and the ULF at moment t_k, respectively; $\otimes_{f_l}$ and $\otimes_{f_u}$ are the combination operators of f_l and f_u, respectively.

Two important reliability indices are used here: loss of load probability (LOLP) and expected un-supplied load (EUL). The LOLP which is the probability of the generating system inability to supply all the load is the expectation of the LLIF

$$L_{\mathrm{OLP}}(t_k) = u'_{f_{\mathrm{l}}}(z = 1, t_k) \tag{34}$$

where $L_{\mathrm{OLP}}(t_k)$ is the LOLP of the generating system at moment t_k.

The EUL indicating the average load curtailment is the expectation of the ULF

$$E_{\mathrm{UL}}(t_k) = u'_{f_{\mathrm{u}}}(z = 1, t_k) \tag{35}$$

where $E_{\mathrm{UL}}(t_k)$ is the EUL of the generating system at moment t_k.

D. ALGORITHM OF SHORT-TERM RELIABILITY ASSESSMENT OF GENERATING SYSTEMS CONSIDERING DR RELIABILITY

The period of short-term reliability assessment and the sampling interval are denoted by T and Δt, respectively. The flow chart of short-term reliability assessment of generating systems considering DR reliability is shown in Fig. 6 and the detail procedure is listed as follows.

Step 1: Initialize the distribution of DRPs' response capacity and GUs' output capacity at moment t_0, and let $k = 0$ and $t_{\mathrm{ass}} = 0$, where k and t_{ass} refer to the order of time intervals and the current time, respectively.

Step 2: If $t_{\mathrm{ass}} \geq T$ is true, assign the value of k to$N$ which is the total number of time intervals during the assessment period, and then jump to Step8; otherwise continue.

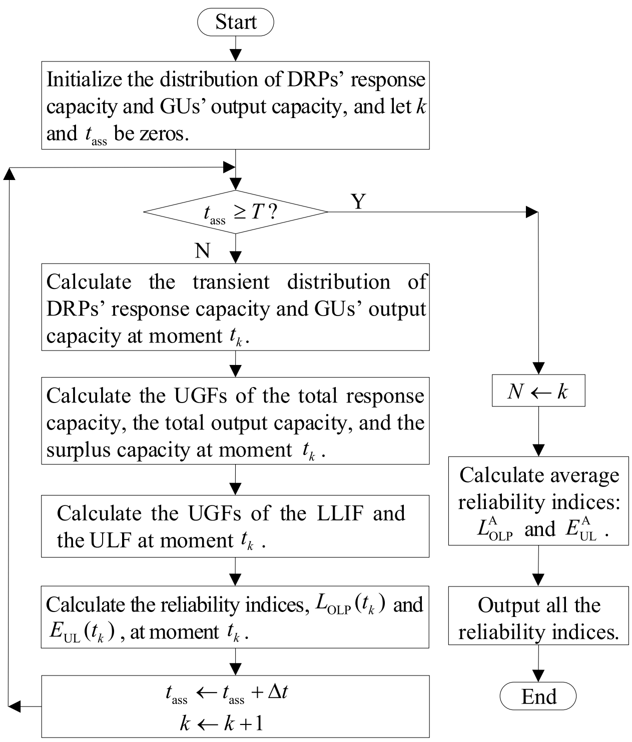

FIGURE 6. Flow chart of short-term reliability assessment of generating systems considering DR reliability.

Step 3: Calculate the transient distribution of DRPs' response capacity and GUs' output capacity at moment t_k, according to (24) and (26), respectively.

Step 4: Calculate the UGFs of the total response capacity of DRPs, the total output capacity of GUs, and the surplus capacity at moment t_k, according to (18), (22) and (29), respectively.

Step 5: Calculate the UGFs of the LLIF and the ULF at moment t_k, according to (32) and (33), respectively.

Step 6: Calculate the reliability indices of generating systems at moment t_k, $L_{\mathrm{OLP}}\ (t_k)$ and $E_{\mathrm{UL}}\ (t_k)$, according to (34) and (35), respectively.

Step 7: Increase t_{ass} by Δt and increase k by one, and then jump to Step2.

Step 8: Calculate the average reliability indices of generating systems during the period of the DR event according to the following equations

$$L_{\mathrm{OLP}}^{\mathrm{A}} = \sum_{k=1}^{N} L_{\mathrm{OLP}}(t_k) \Big/ N \tag{36}$$

$$E_{\mathrm{UL}}^{\mathrm{A}} = \sum_{k=1}^{N} E_{\mathrm{UL}}(t_k) \Big/ N \tag{37}$$

where $L_{\mathrm{OLP}}^{\mathrm{A}}$ and $E_{\mathrm{UL}}^{\mathrm{A}}$ are the average values of LOLP and EUL during the period of the DR event, respectively.

Step 9: Output all the reliability indices of the generating system, including the time-varying and the average reliability indices.

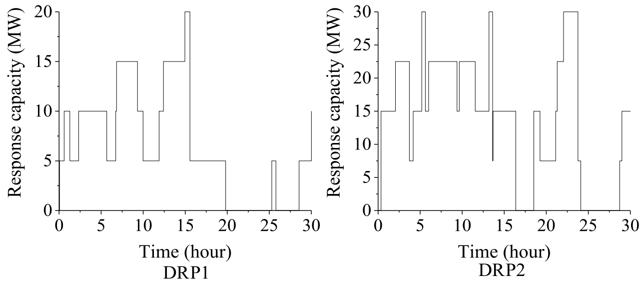

FIGURE 7. Sequences of DR response capacity of DRP1 and DRP2.

VI. CASE STUDY

The generating system of IEEE-RTS79 reliability test system [41] consists of 32 GUs with capacity ranging from 12 to 400MW and its loads are expressed in hourly chronological fashion, the peak value of which is 2850MW. In [41], each GU is represented by a two-state model consisting of normal and failure states. And the transition rates of GU output capacity, i.e. the failure rate and the repair rate of each GU, are shown in Table 3.

Suppose that two DRPs, which are represented by DRP1 and DRP2, respectively, are added into this system. Fig. 7 shows parts of response capacity sequences from those two DRPs, partially revealing the state transition characteristics of DR response capacity. The minimum and maximum values of DRP1's response capacity are 0 and 20.6MW, respectively, and those of DRP2's response capacity are 0 and 30.2MW, respectively.

A. APPROPRIATE STATE NUMBER OF DRP's RESPONSE CAPACITY

The sum of squared distances (SSD) [42] from data points to their corresponding clusters' centers is the most intuitive and frequently used criterion function to find the optimal cluster number. And hence we use it to choose the appropriate state number of response capacity. The SSDs for different partitions obtained by the method of the MSD classification are shown in Fig. 8.

The location of an elbow in the plot is generally considered as an indicator of the appropriate number of states. As shown in Fig. 8(a), the value of SSD decreases as state number increases, but it can be seen an elbow at the state number of three. This elbow indicates that additional clusters beyond the third have little value. In the same way, as illustrated in Fig. 8(b), an elbow appears at the state number of three. Therefore, the appropriate state numbers of the response capacity of DRP1 and DRP2 are both three.

B. MODELLING OF DR RELIABILITY

Take DRP1 as an example to explain the state division process of DR response capacity. As shown in Fig. 8(a), the appropriate state number of DRP1 is three, so we perform the state division according to Table 1 and obtain the results of state division shown in Table 4, where $\bar{D}$ and S are 8.616 and

TABLE 3. Transition rates of GU output capacity.

Transition Rate	oil 12 MW	oil 20 MW	hydro 50 MW	coal 76 MW	oil 100 MW	coal 155 MW	oil 197 MW	coal 350 MW	nuclear 400 MW
failure rate (10^{-4} f/h)	3.40	22.22	5.05	5.10	8.33	10.42	10.53	8.70	9.09
repair rate (10^{-4} f/h)	1.67	2.00	5.00	2.50	2.00	2.50	2.00	1.00	0.67

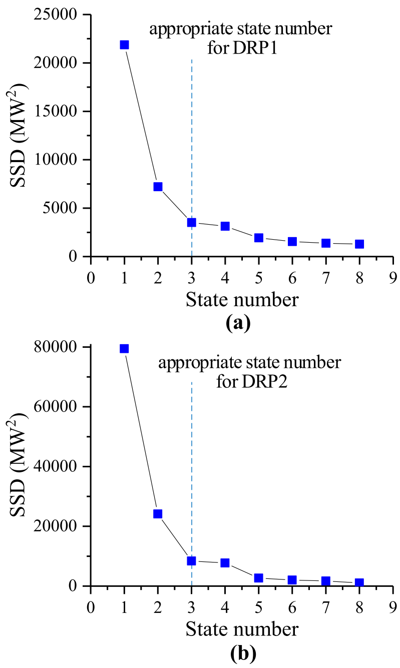

FIGURE 8. SSDs for different partitions. The location of an elbow in the plot is generally considered as an indicator of the appropriate state number. (a)SSD of DRP1, (b) SSD of DRP2.

TABLE 4. State division of DRP1's response capacity when N_D is three.

State, i	Interval, E_i
1	$[D_{\min}, \bar{D}-S/2)$
2	$[\bar{D}-S/2, \bar{D}+S/2)$
3	$[\bar{D}+S/2, D_{\max}]$

5.112 MW, respectively, obtained from (6) and (7); $D_{\min}$ and D_{max} are 0 and 20.6 MW, respectively.

Then the performance level of DRP1's response capacity in each state is calculated out by (8) and shown in Table 5 which also displays the total residence time in each state. And the numbers of the transitions between different states during the total residence time $T_i (i = 1, 2, 3)$ are shown in Table 6.

Then the transition matrix of DRP1's response capacity is calculated out according to (9) and (10), and shown in Table 7. Likewise, the transition matrix of DRP2's response capacity can also be obtained and shown in Table 7.

TABLE 5. Performance levels and total residence time of DRP1's response capacity in each state when N_D is three.

State, i	Performance level, $\bar{D}_i$ (MW)	Total Residence time, T_i (hour)
1	3.60	336
2	10.00	184
3	16.12	107

TABLE 6. Numbers of transitions between different states of DRP1's response capacity when N_D is three.

State, i	1	2	3
1	-	174	0
2	103	-	81
3	70	10	-

If $\mathbf{p}_{\mathrm{D}}(t_0)$, the initial distribution of DRP1's response capacity, is (1,0,0) and the sampling interval Δt is one hour, according to (23), the transition probability matrix $\mathbf{P}_{\mathrm{D}}(\Delta t)$ is

$$\mathbf{P}_{\mathrm{D}}(\Delta t) = \begin{pmatrix} 0.6846 & 0.2599 & 0.0555 \\ 0.3511 & 0.4526 & 0.1963 \\ 0.3812 & 0.1241 & 0.4947 \end{pmatrix} \tag{38}$$

Let t_0 be 8409, and then the time-varying transient distribution of DRP1's response capacity can be obtained through (24) and shown in Fig. 9.

Then the UGFs of DRP1's response capacity can be obtained according to (16). For example, the UGF at moment 8412 is

$$u_{D_1}(z, 8412) = 0.5484z^{3.60} + 0.3024z^{10.00} + 0.1492z^{16.12} \tag{39}$$

C. SHORT-TERM RELIABILITY ASSESSMENT OF GENERATING SYSTEMS CONSIDERING DR RELIABILITY

Suppose that these DR resources will be committed during the period from the 8409th to the 8421th time interval, when the peak load of 2850MW will appear; and that all the generator units are in normal states and the initial distributions of the two DRPs' response capacity are both (1, 0, 0) at the beginning of the reliability assessment. The time-varying short-term reliability of the generating system during the period is accessed by the method in the paper and the results are shown in Fig. 10. As can be seen from Fig. 10, the reliability

TABLE 7. Transition matrices of DRP1's and DRP2's response capacity.

DRP1 (f/h)		To state		
		3.60 MW	10.00 MW	16.12 MW
	3.60 MW	-0.5179	0.5179	0.0000
From state	10.00 MW	0.5598	-1.0000	0.4402
	16.12 MW	0.6542	0.0935	-0.7477
DRP2 (f/h)		To state		
		5.06 MW	15.00 MW	26.08 MW
	5.06 MW	-0.7273	0.5215	0.2058
From state	15.00 MW	0.3681	-1.0000	0.6319
	26.08 MW	0.3818	0.3318	-0.7136

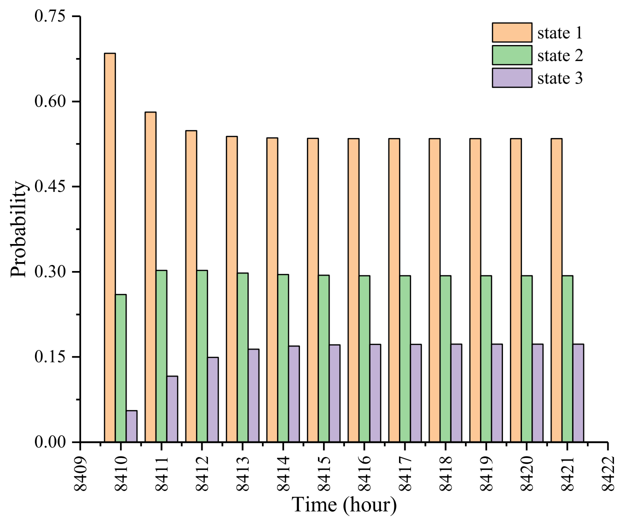

FIGURE 9. Time-varying transient distribution of DRP1's response capacity. The sum of the probabilities of the three states at any time interval is one.

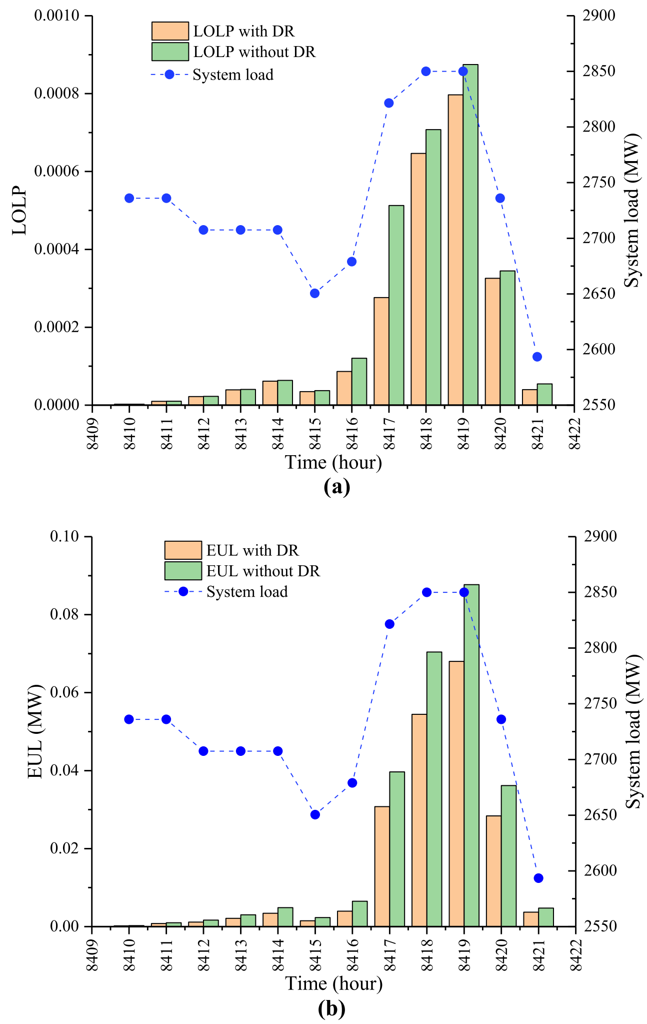

FIGURE 10. Time-varying reliability indices and loads during the DR event. (a) LOLP and loads, (b) EUL and loads.

of the generating system is improved, i.e. LOLP and EUL are reduced due to the participation of DR. And decrease percentages of reliability indices are shown in Fig. 11. It can be observed that the largest decrease percentages of LOLP and EUL occur at the moments of 8417 and 8416, respectively, not coinciding with the time intervals when the peak-load occurs.

Also, as shown in Fig. 10, the reliability indices do not always increase with the growth of the system load. For instance, (i) although the system load level at the 8412th time interval is lesser than that at the 8411th time interval, the reliability indices at the 8412th time interval are greater than those at the 8411th time interval; (ii) although the system load levels at the 8418th and the 8419th time intervals are the same, i.e. 2850MW, the reliability indices at the two time intervals are different. Take LOLP as an example to explain these phenomena. The reliability indices of generating systems depend on both the system load level and the equivalent generating capacity which is the sum of DRPs' response capacity and GUs' output capacity, not on the load level alone. The difference between the equivalent generating capacity and the load level is known as surplus capacity and its cumulative distribution functions (CDF) at the above-mentioned time intervals are shown in Fig. 12.

It can be seen that the CDF value of zero surplus capacity at the 8412th time interval is larger than at the 8411th time interval, so LOLP at the 8412th time interval is greater than at the 8411th time interval. Similarly, the CDF value of zero

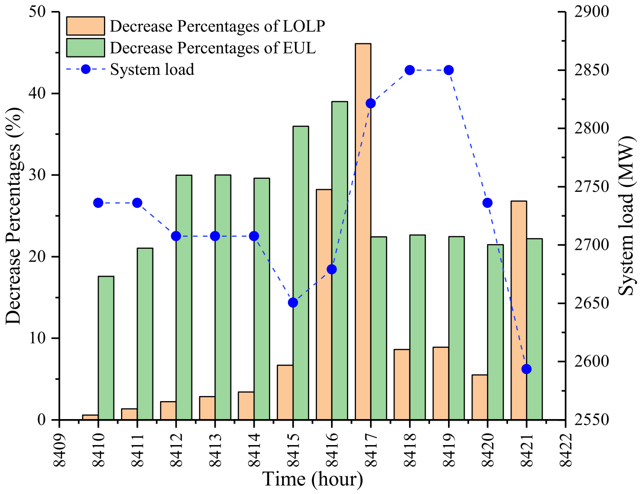

FIGURE 11. Time-varying loads and decrease percentages of reliability indices.

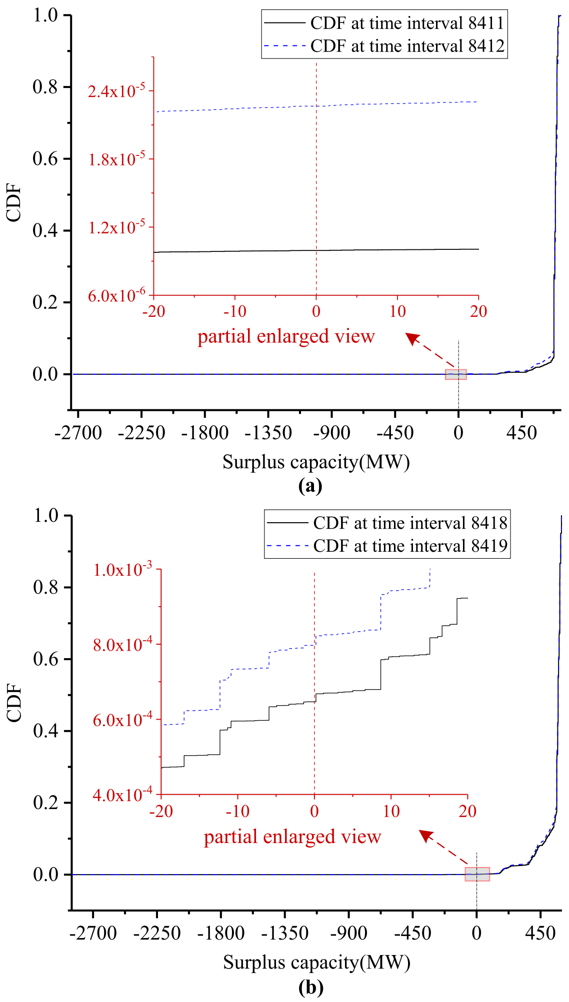

FIGURE 12. CDFs of surplus capacity. (a) CDFs at the 8411th and 8412th time intervals, (b) CDFs at the 8418th and 8419th time intervals.

surplus capacity at the 8419th time interval is larger than at the 8418th time interval, so LOLP at the 8419th time interval is greater than at the 8418th time interval.

TABLE 8. Average reliability indices during the period of the DR event.

Average Reliability Indices	LOLP	EUL (MW)
without DR	2.15E-04	1.99E-2
with DR	1.80E-04	1.53E-2
decrease percentage	16.28%	23.12%

TABLE 9. Performance levels and transition matrices of DRP1's and DRP2's response capacity.

DRP1 (f/h)		To state			
		0.00 MW	5.02MW	10.04MW	16.12MW
From state	0.00MW	-1.0000	1.0000	0.0000	0.0000
	5.02MW	0.2810	-1.0000	0.7190	0.0000
	10.04MW	0.0924	0.4674	-1.0000	0.4402
	16.12MW	0.0748	0.5794	0.0935	-0.7477

DRP2 (f/h)		To state				
		0.00MW	7.53MW	15.04MW	22.52MW	29.36MW
From state	0.00MW	-1.0000	0.5588	0.4412	0.0000	0.0000
	7.53MW	0.1347	-1.0000	0.5603	0.3050	0.0000
	15.04MW	0.1044	0.2637	-1.0000	0.3352	0.2967
	22.52MW	0.1217	0.1652	0.2609	-0.9913	0.4435
	29.36MW	0.1428	0.3429	0.4095	0.1048	-1.0000

The average reliability indices of the generating system during the period of the DR event are shown in Table 8, which also reveals that the participation of DR improves the reliability of the generating system, i.e. decreases reliability indices.

D. EFFECT OF STATE NUMBER OF RESPONSE CAPACITY ON GENERATING SYSTEM RELIABILITY

Supposing one 4-state and one 5-state CTMC models are applied to the reliability modelling of DRP1's and DRP2's response capacity, respectively, the performance level of response capacity in each state and the transition matrices are shown in Table 9.

In order to reveal the effect of the state number of response capacity on reliability indices, we consider two conditions: one using two 3-state models to represent the response capacity of DRP1 and DRP2, the other using one 4-state model and one 5-state model to represent the response capacity of DRP1 and DRP2, respectively. And the time-varying reliability indices during the DR event in those two conditions are shown in Fig. 13, from which it can be seen that the differences of reliability indices in those two conditions are minuscule. The results also verify the correctness of the above-mentioned appropriate state numbers.

E. RELIABILITY INDICES UNDER DIFFERENT INITIAL CONDITIONS

The proposed method in this paper can reflect the effect of initial conditions on reliability indices. Firstly, we consider

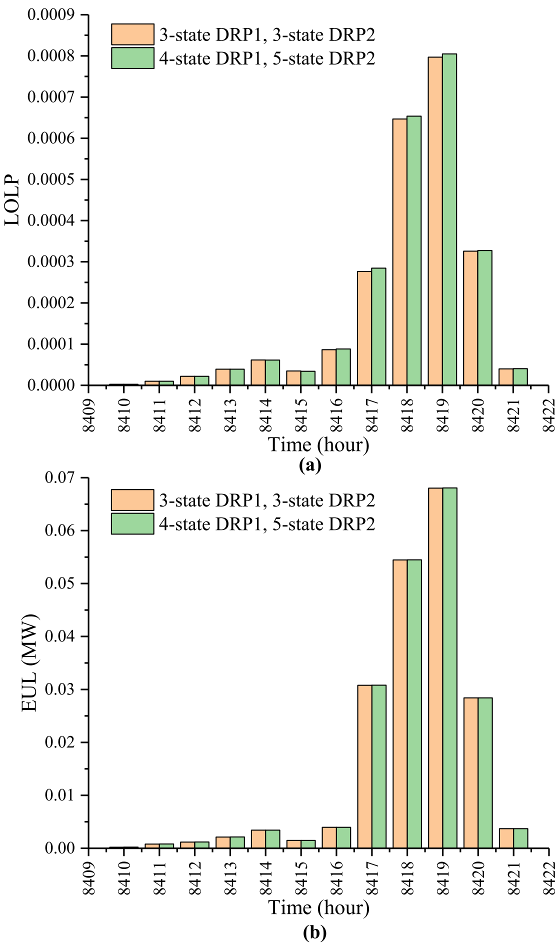

FIGURE 13. Comparation of time-varying reliability indices with different state numbers. Two conditions are considered: one using two 3-state models to represent the response capacity of DRP1 and DRP2, the other using one 4-state model and one 5-state model to represent the response capacity of DRP1 and DRP2, respectively. (a) Comparation of LOLP, (b) Comparation of EUL.

different initial conditions of DRPs. Take the above-mentioned 3-state models of DRP1's and DRP2's response capacity as an example and suppose that all the generator units are in the normal states. We consider two initial conditions: one supposing that the initial states of DRP1 and DRP2 are both the first state, i.e. their initial distributions are both (1,0,0); the other supposing that the initial states of DRP1 and DRP2 are both the third state, i.e. their initial distributions are both (0,0,1). The percentage changes of the reliability indices from the first initial condition to the second initial condition are shown in Fig. 14. Take the EUL at time interval 8412 as an example to illustrate the calculation of percentage changes. The values of EUL at time interval 8412 under the first and the second conditions are 0.001162 and 0.001130 MW, respectively, so the percentage change of EUL at time interval 8412 is

$$\left((0.001130 - 0.001162)/0.001162\right) \times 100\% = -2.754\% \tag{40}$$

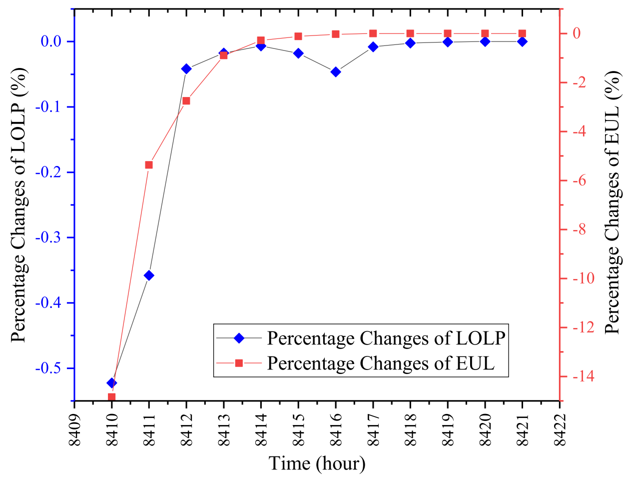

FIGURE 14. Percentage changes of the reliability indices due to the change of DRP's initial condition from the first to the second initial condition. The first initial condition supposes that the initial states of DRP1 and DRP2 are both the first state, i.e. their initial distributions are both (1,0,0); the second initial condition supposes that the initial states of DRP1 and DRP2 are both the third states, i.e. their initial distributions are both (0,0,1).

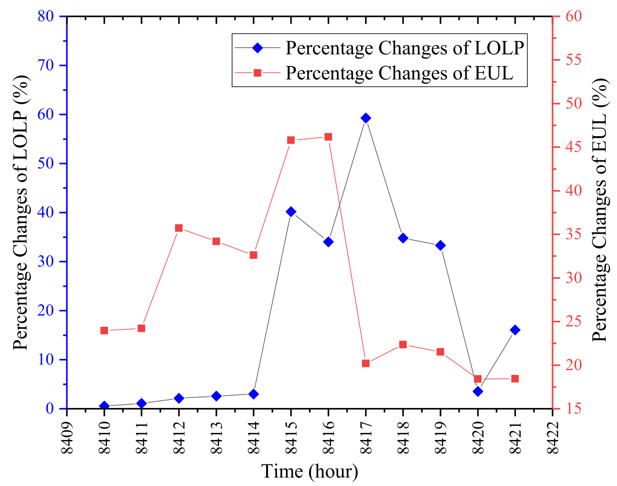

FIGURE 15. Percentage changes of the reliability indices due to the change of GU's initial condition from the first to the second initial condition. The first initial condition supposes that all the generator units are in the normal states; the second initial condition supposes that all the generator units are in the normal states except an oil-fired GU with the rated capacity of 20MW, which is in the failure state at the initial moment.

As shown in Fig. 14, the percentage changes of the reliability indices are negative, indicating that reliability indices reduce with the initial condition changing from the first to the second condition.

Then consider different initial conditions of GUs and suppose that the initial distributions of the two DRPs are both (1,0,0). We consider two initial conditions of GUs: one supposing all the generator units are in the normal states, the other supposing that all the generator units are in the normal states except an oil-fired GU with the rated capacity of 20MW, which is in the failure state at the initial moment. The percentage changes of the reliability indices from the first initial condition to the second initial condition are shown in Fig. 15.

It can be seen that the percentage changes of the reliability indices are positive, indicating that the reliability indices increase with the initial condition changing from the first to the second condition.

VII. CONCLUSION

This paper proposes a novel DR reliability model to assess the reliability of generating systems during a DR event. The short-term reliability model of DR response capacity is represented by a multi-state CTMC. On this basis, the sequence of DR response capacity is classified into several states by the method of MSD classification, and the transition matrix and the transient distribution of DR response capacity are estimated. The CTMCs of both DR response capacity and GU output capacity are converted into UGFs by *Lz*-transform. Then the algorithm to assess the short-term reliability of generating systems considering DR reliability during a DR event is presented. Finally, the above process is verified by a study case. Results obtained from this paper can be summarized in the following aspects:

(i) The time-varying and the average reliability indices of generating systems obtained through the proposed method in the paper can evaluate the operating risk of generating systems during the period of DR events.

(ii) The change trend of the operating risk of a generating system does not coincide exactly with that of the load level, because the risk represented by reliability indices depends on the combination of load levels, GU output capacity and DR response capacity, not on load levels alone.

(iii) The MSD classification is a feasible method for the state division of DR response capacity and the appropriate state number can be found by the SSD criterion.

(iv) The proposed algorithm of short-term reliability assessment of generating systems considering DR reliability can reflect the effect of initial conditions of DRPs and GUs on reliability indices.

In further research, the presented approach will be extended to composite generation-transmission systems taking network constraints into account, and include periods after DR events to think of shifted loads and DR rebounds.

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