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Intra-Day Dynamic Network Reconfiguration Based on Probability Analysis Considering the Deployment of Remote Control Switches

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ABSTRACT With the continuous development of renewable distributed generation (DG) in distribution network, the effective integration of DGs to make system operation safe and economic has become a major concern. Dynamic network reconfiguration, which relies on the remote control switches, is being considered as an efficient method to solve the above problem. An optimal model of intra-day dynamic reconfiguration is proposed to maximize the accommodation revenue of DGs and minimize the operation cost of distribution network considering the deployment constraint of remote control switches. Besides the traditional constraints, the number of remote control switches and their action times are considered as the constraints and checked before calculating the reconfiguration model which can improve the efficiency of reconfiguration. In order to solve the dynamic reconfiguration model, time period reduction strategy and decimal coding strategy are developed to improve the coding efficiency, and tree coding is adopted to test the radiation of distribution network. In addition, a probabilistic analysis method is used to deal with the randomness of DGs. Finally, the feasibility and effectiveness of the proposed model are verified by the IEEE33 node system.

INDEX TERMS Intra-day dynamic reconfiguration, probabilistic analysis method, remote control switch constraint, time period reduction.

I. INTRODUCTION

The energy shortage and environmental pollution are becoming more and more serious due to the large consumption of traditional energy [1]. There is a growing demand for renewable distributed generation (DG) to integrate into the grid due to clean energy supply [2]. With the high proportion of DG, the network reconfiguration is becoming greatly important to ensure the safety and economic operation of the grid. For network reconfiguration, there are some aspects such as load and DG's output that need to be considered due to their randomness [3]. The network reconfiguration is affected by a large number of DGs integrated into the distribution network, and the operation cost is much higher because of the excessive action number of remote control switch, which causes the life reduction of the switch, and reduces the reliability of the system [4].

The dynamic reconfiguration of the distribution network as an important management strategy is to dynamically select a topology of the distribution network to optimize the performance criteria, e.g., network losses and voltage profile. There are two main advantages of dynamic reconfiguration: (1) minimize the curtailment of wind and solar power, or maximize the consumptive power of DG, thereby improving the penetration of DG; (2) reduce the negative impacts of DG integration, such as over-voltage problem, power flow unbalanced distribution problem, energy balance problem, etc. In [5], the influence of network reconfiguration was addressed, and the optimization deployment model with DG and energy storage system was proposed to maximize the integration of DG. The optimal switching schedule was discussed to minimize the power losses in [6], where the network

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topology is optimized by network reconfiguration. In [7], the feeder reconfiguration and the capacitor switching were addressed to optimally reduce the operation cost of the power grid, including the electricity purchase cost, penalty cost for power outage, transformer losses cost, and switching operation cost. The over-voltage problem caused by the high proportion of DG integrated in the distribution network can be solved by the dynamic reconfiguration [8]. In [9], optimal static reconfiguration and dynamic reconfiguration were considered as active distribution network management strategies with voltage control, power factor control, and energy reduction.

As for the solution of dynamic reconfiguration model, the problems such as the randomness of DG output power, and the deployment of remote control switches are needed to be considered. In [10], the uncertainty modeling techniques are concluded into six aspects, i.e., probabilistic, stochastic optimization, robust optimization, possibilistic, hybrid probabilistic-possibilistic, and information gap decision theory.

The dynamic reconfiguration problem was formulated as a two-stage robust optimization model to minimize losses and DG curtailment in [11] and [12]. In [13], the mixed integer nonlinear problem of dynamic reconfiguration model was transformed into the mixed integer linear programming problem, where the Lagrange method was used for further heuristic optimization. In [14], a novel probabilistic Distribution Feeder Reconfiguration (DFR) based method is proposed to consider the uncertainty impacts into account with high accuracy. A probabilistic generation-load model that considers possible operation scenarios with the probability of the scenarios was established to deal with the uncertainties of DG output power and load in [15]. Stochastic model predictive control was applied to deal with the uncertainty and randomness of new energy output in intra-day dynamic reconfiguration in [16].

Probabilistic methods are used to deal with the uncertainty of DG in the above literatures. However, most probabilistic methods use robust method to make sure their result can adapt the worst situation. The robust method is very conservative and the result obtained by the methods may not meet the economic requirements. A probabilistic analysis method considering many scenarios is needed to get the better revenue under the acceptable risk.

Dynamic reconfiguration mainly depends on the operation of remote control switches. In [17], the output power control and the remote control switch control were used to minimize DG curtailment and reduce the negative impacts of DG integration such as line congestion and over-voltage issues. In [18], the number of switchings was considered as the object of the reconfiguration model. The operation cost of the distribution network can be reduced by decreasing the number of switchings. However, in the literatures, it is often assumed that all the switches in the distribution network were remotely controlled. This is impractical and uneconomical because it is hard to realize the massive deployment of remote control switches in a short period of time. Therefore, it is important to select some switches as the remote control switch. In [19], the critical switches in reconfiguration were identified as the remote control switch by extensive simulations. In [9], the switches operated in the reconfiguration were defined as remote control switches with the limited number and location. In [20], an oppositional differential search algorithm was used to optimize the number and location of remote control switch. In order to realize the intra-day reconfiguration, the remote control switches should be selected according to the conditions of all day instead of some fixed time frame. Besides, the frequent switch operation will cause an increase of system operation cost. Therefore, the operation number of remote control switch should be considered as a constraint.

In order to decrease the number of switchings, one of the effective methods is time period reduction [21]–[25]. The time period reduction method includes threshold method, multi-agent method, systematic index method, monotonicity method, fuzzy C-means clustering method, and information entropy method. The fuzzy C-means clustering method is usually used to solve the problem [25]–[28]. However, In the fuzzy C-means clustering method, the quadratic return of the time period is required. In this paper, a time period reduction strategy combined with the advantages of fuzzy C-means clustering algorithm is proposed, and the state change of each node load in each time period is considered.

In this paper, an intra-day dynamic reconfiguration model is established considering the accommodation of DG integration and the operation cost of distributed network. The contributions are as follows:

1. An intra-day dynamic reconfiguration model based on probabilistic analysis is established to optimize the operation of network in one day.
2 . The remote control switch constraint is proposed according to the time period reduction strategy. The constraint is performed before the calculation of dynamic reconfiguration model, which can improve the efficiency of the reconfiguration.
3. Decimal coding strategy based on time period reduction is proposed to dramatically decrease the order of magnitude of solution which can increase the efficiency of coding and decrease the calculation time.
4. Radiation check strategy using tree-structure coding is proposed which is convenient for computers to check the radiation of distribution network.

The paper is organized as follows: In Section II, the problem formulation is presented. The optimization strategies used in dynamic reconfiguration are addressed in Section III. The proposed model and strategies are verified in Section IV. Finally, the conclusions are drawn in Section V.

II. PROBLEM FORMULATION

A. PROBABILISTIC ANALYSIS MODEL

In the existing research of dynamic reconfiguration, the output of DG is usually treated as a definite value according to its output function, which results in that the volatility and uncertainty of the DG output are ignored. Therefore, the probabilistic analysis model is used to consider the volatility and uncertainty of DG. We assume that the error between the actual output value and the predicted value of DG in each time period belongs to normal distribution. According to the prediction information of weather data day-ahead, the predicted output value range of DG with a certain confidence level is obtained. In this condition, the actual output of DG is expressed in (1).

$$P_R\left\{\overline{P}_{DGn,t}-\hat{P}_{DGn,t}\le P_{DGn,t}\le\overline{P}_{DGn,t}+\hat{P}_{DGn,t}\right\}\ge\alpha,\quad \forall n\in N,\quad \forall t\in T \tag{1}$$

where $P_R\{\cdot\}$ represents a probabilistic function; $\overline{P}_{DGn,t}$ represents the predicted output value of DG; $\overline{P}_{DGn,t}$ represents the deviation between the predicted value $\overline{P}_{DGn,t}$ and the actual value $P_{DGn,t}$ at the confidence level α. The deviation value can be expressed as a percentage of the predicted value [13]. Here, the deviation value of DG is set as 20% of the predicted value.

According to the $\hat{P}_{DGn,t}$ and α, the mean value $\mu_{n,t}$ and the standard deviation $\sigma_{n,t}$ of a DG output's distribution can be obtained. If the $\overline{P}_{DGn,t}-\hat{P}_{DGn,t}$ is directly used as the output value, the dynamic optimal reconfiguration model will be solved using the minimum output of DGs compared with the actual output, which means that the model is solved under the worst condition of the DG's output, and the result is quite conservative. Therefore, the probabilistic analysis model is used to avoid the conservatism. In this paper, the total output of DGs is sampled randomly in each time period according to the distribution obtained by the above method. Besides, fuzzy C-means clustering algorithm is used to analyze the distributed generation output in different time periods. The main steps are as follows:

1. The total output of DGs in each time period is treated as a random variable, which is described by the normal distribution.

$$\begin{aligned}\mu_{G,t}&=\sum_{n\in N}\mu_{n,t}\\ \sigma_{G,t}&=\left(\sum_{n\in N}\sigma_{n,t}^2\right)^{\frac{1}{2}},\quad \forall t\in T\end{aligned} \tag{2}$$

where $\mu_{G,t}$ represents the mean value of the distribution; $\sigma_{G,t}$ represents the standard deviation of the distribution.

2. Random sampling of DG for each time period is performed according to the constraint (3):

$$P_R\left\{\underline{P}_{G,t}\le\sum_{n\in N}P_{DGn,t}\le\overline{P}_{G,t}\right\}\ge\beta,\quad \forall t\in T \tag{3}$$

where $\underline{P}_{G,t}$ and $\overline{P}_{G,t}$ represent the lower and upper limits of the total output of DG in random sampling process respectively; β represents the confidence level in random sampling.

3. After random sampling, the sample set Ω_s is obtained, and the fuzzy C-means clustering algorithm is used to calculate all samples in Ω_s. Each cluster center is an output prediction value of DG in a corresponding scene. The probability of the output value is obtained by (2), and the probability of the output value in each scene is normalized to obtain the occurrence probability of each scene. In this condition, the scenes of 24-hour periods of DG output prediction value are carried out, and the scene set SC_t ($\forall$t$\in$T) of each time period is obtained.

B. OBJECTIVE FUNCTION

The dynamic optimal reconfiguration model of distribution network is proposed based on the probabilistic analysis, considering the revenue of DG and the operation cost of distributed network. The operation cost includes the cost of network losses, the cost of switching operation, and the cost of energy outage. Considering the randomness and uncertainty of DG, the active-power output of DG in each period is analyzed under multiple probabilistic scenarios. The objective function is constructed by maximizing revenue and minimizing operating cost, as shown in (4).

$$\max F=\sum_{t\in T}\sum_{sc\in SCt}\frac{F_{t,sc}^{hc}}{F_{t,sc}^{op}}p_{sc} \tag{4}$$

where $F_{t,sc}^{hc}$ and $F_{t,sc}^{op}$ represent the revenue of DGs and the operation cost of network under the scene sc at time interval t, respectively; T represents the time interval set of the day; SCt represents the set of scenes in which DGs have different output values. p_{sc} represents the occurrence probability of the scene sc.

The revenue of DG is calculated by (5):

$$F_t^{hc}=\sum_{n\in N}C_{dg,n}P_{n,t} \tag{5}$$

where N represents the set of DGs; $C_{dg,n}$ represents the unit revenue of DG's active-power output; $P_{n,t}$ represents the active-power output of the DG n at time interval t.

The operation cost of the network is expressed in (6):

$$F_t^{op}=C_{loss,t}E_{loss,t}+\sum_{l\in L_t}C_{sw}\left|s_{l,t}-s_{l,t-1}\right|+C_{ens}ENS_t \tag{6}$$

where $C_{loss,t}$ and $E_{loss,t}$ represent the unit price and network losses at time interval t, respectively; L_t represents the set of remote control switches in the distribution network; C_{sw} represents the single switching cost; $s_{l,t}$ represents the opening or closing state of switch l at time interval t, where opening corresponds 0 and closing corresponds 1; C_{ens} represents the unit cost of energy outage; ENS_t represents the energy outage of the distribution network at time interval t.

Time-of-use is adopted as the unit electricity price at each time interval. The network losses and the energy outage are expressed in (7) and (8). The outage value of load is calculated based on the remote control switches set. The remote control switches divide the load nodes in the distribution network into several regions, and the load nodes in each region have the same blackout characteristics.

$$E_{loss,t} = P_{loss,t} \cdot \Delta t = \sum_{l \in L_t} R_l \frac{(P_l)^2 + (Q_l)^2}{(U_l)^2} \cdot \Delta t \tag{7}$$

where R_l, P_l, Q_l, U_l represent the branch resistance, active power, reactive power and voltage of the branch l, respectively; Δt represents the duration of each period of time.

$$ENS_t = \sum_{l \in L_t} \lambda_l \cdot N_l \cdot P_l \cdot t \tag{8}$$

where λ_l represents the fault rate of branch l; N_l represents the length of branch l; P_l represents the outage load caused by branch l fault; t represents the fault time of branch l.

C. CONSTRAINTS

1) CONSTRAINTS ON REMOTE CONTROL SWITCHES

a) Number of Remote control switches Constraints

$$\sum_{sw \in SW} s_{sw} \le N_{RCS} \tag{9}$$

where SW represents the set of switches in the distribution network; S_{sw} represents the state of the switch sw, where 0 corresponds non-selected state and 1 corresponds selected state; N_{RCS} represents the maximum number of remote control switches.

In the intra-day dynamic reconfiguration model, the total number of remote control switches is limited not more than N_{RCS} in all time periods. In order to avoid obtaining the impracticable and uneconomic result when selecting remote control switches, the set of remote control switches to be selected in this paper is based on the results of 24-hour static reconfiguration, which ensures the rationality of the remote control switches set.

b) Number of Switching Times Constraints

$$\sum_{t \in T} s_{sw,t} \le N_{\max}, \quad \forall sw \in SW \tag{10}$$

$$\sum_{sw \in SW} \sum_{t \in T} s_{sw,t} \le N_{total\,\max} \tag{11}$$

where N_{max} represents the upper limit of the number of intra-day operations for a single remote switch; $S_{sw,t}$ is the number of operations for the remote switch sw in time t; $N_{totalmax}$ represents the upper limit of the total number of intra-day operations for all remote switches. N_{max} is related to the service life and the maximum effective number of switchings. Assuming that the remote control switch has a service life of 10 years and the maximum effective number of switchings is 10,000 times, N_{max} is 3 times.

2) CONSTRAINTS ON INTRA-DAY DYNAMIC RECONFIGURATION

a: NETWORK TOPOLOGY CONSTRAINT

In dynamic reconfiguration, the distribution network operates radially, which requires that the topology of the distribution network must include all nodes, no islands and no ring networks in each time period. In this paper, the loop-based decimal coding method is adopted to verify the radiation and the method is described in detail in section III.

b: POWER FLOW EQUILIBRIUM CONSTRAINTS

The power flow equilibrium constraints in dynamic reconfiguration are expressed in (12).

$$\begin{cases} \sum_{i \in I} P_{Li,t} + P_{loss,t} = \sum_{n \in N} P_{DGn,t} + P_{s,t} \\ \sum_{i \in I} Q_{Li,t} + Q_{loss,t} = \sum_{n \in N} Q_{DGn,t} + Q_{s,t} \end{cases}, \quad \forall t \in T \tag{12}$$

where I represents the set of nodes; $P_{Li,t}$ and $Q_{Li,t}$ represent the active power load and reactive power load; $P_{loss,t}$ and $Q_{loss,t}$ represent the active power losses and reactive power losses; $P_{DGn,t}$ and $Q_{DGn,t}$ represent the active power and reactive power output of DG; $P_{s,t}$ and $Q_{s,t}$ represent the active power and reactive power injected from the upper layer network or the generation in the distribution network.

c: DISTRIBUTED GENERATION OUTPUT CONSTRAINTS

$$\begin{cases} 0 \le P_{DGn,t} \le P_{DGn,\max} \\ 0 \le Q_{DGn,t} \le Q_{DGn,\max}, \end{cases} \quad \forall n \in N, \ \forall t \in T \tag{13}$$

where the power factor is 0.9; $P_{DGn,max}$ and $Q_{DGn,max}$ represent the upper limit of DG's active power and reactive power output. It is assumed that the power factor of wind turbine and photovoltaic are kept constant by using reactive power compensation equipment.

d: NODE VOLTAGE CONSTRAINT

The node voltage constraint in distribution network is expressed as constraint (14).

$$U_{i,\min} \le U_{i,t} \le U_{i,\max}, \quad \forall i \in I, \ \forall t \in T \tag{14}$$

where $U_{i,\min}$ and $U_{i,\max}$ represent the lower and upper limit of the node voltage.

e: Branch Current Constraint

$$I_{l,t} \le I_{l,\max}, \quad \forall l \in L_t, \ \forall t \in T \tag{15}$$

where $I_{l,max}$ represents the upper limit of branch current.

The capacity of distribution networks to accommodate DGs is different because of different network topology. For a given distribution network topology, when the branch current exceeds the constraint, the output of DG has to be restricted to satisfy the maximum current constraint of the branch.

III. OPTIMIZATION STRATEGIES

In the process of solving the intra-day dynamic optimization reconfiguration model, several optimization strategies are proposed in this paper, including time period reduction strategy, branch coding strategy based on time period reduction, and radiation check strategy. The coding efficiency and model solution speed are improved by the time period reduction strategy and the branch coding strategy. The effectiveness of the reconfiguration scheme is ensured by the radiation check strategy.

A. TIME PERIOD REDUCTION STRATEGY

Because of the constraints of the number of remote control switches and the times of switching operations, if the remote control switches are selected from the 24-hour static reconfiguration results directly, the constraints will be not satisfied. Furthermore, the solving efficiency is very low. Therefore, the strategy of time period reduction is adopted in this paper. According to the inherent similarity of load characteristics in each node, the adjacent time periods with high similarity are combined, and the same code is adopted in the fusion period to improve the coding efficiency. The time period reduction strategy is as follows:

1. The equivalent load of one day is divided into 24 periods, and the load of each node remains unchanged in each time period.
2. The 24 periods in one day are scheduled to be reduced into M segments. The sum of the difference between the complex power vector of 24 periods and the mean complex power vector of its corresponding segment is taken as the objective function of the reduction strategy, as shown in (16).

$$\min f = \sum_{t=1}^{24} \left| \boldsymbol{x}_{t,m} - \boldsymbol{v}_m \right|, \quad (m=1, 2, \cdots, M) \tag{16}$$

   where $\boldsymbol{x}_{t,m}$ represents the load power column vector of n nodes in t_{th} time period and m_{th} time segment; n represents the number of nodes in distribution network; $\boldsymbol{v}_m$ represents the average complex power column vector of n nodes in the m_{th} time segment.
3. Genetic algorithm is used to solve the above time period reduction model, and the starting time of each segment can be obtained, which can be used to solve the optimization model of intra-day dynamic reconfiguration.

B. BRANCH CODING STRATEGY BASED ON TIME PERIOD REDUCTION

The loop-based decimal coding method is used to code the branch switches. Taking the IEEE33 node system as an example, there are five loops in the network due to the existence of the five interconnection switches, as shown in Fig. 1. In the process of the loop-based decimal coding, the branch switch which does not be presented in any loops does not be coded. In the five loops, one switch is chosen as the open state switch in each loop respectively. Although the binary coding method and the decimal coding method are the two main methods of branch coding in dynamic optimization reconfiguration. However, the binary coded space is 2^{37} because the system has 37 branches. It is much higher than that of decimal coding. Compared with the binary method, the calculation times of the decimal method is greatly reduced, and the proportion of feasible solution are improved.

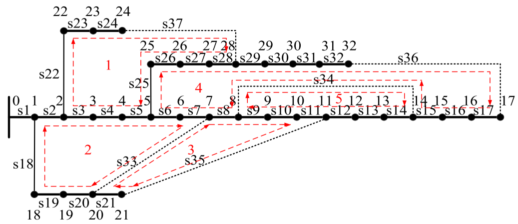

FIGURE 1. IEEE33 node system.

The coding strategy based on time period reduction is adopted in this paper. At first, each time segment is coded, and the code of each time period in the same time segment are the same. Secondly, in each time segment, the loop-based decimal coding method is adopted to code the branch switch in the set of remote control switches, and the code of remote control switches is used for radiation check. If the constraints on remote control switches are satisfied, the code can be set as a feasible solution. Finally, a matrix is used to record the opening and closing states of each switch at each time segment.

In the previous literature of dynamic configuration model solved by time period division method, the constraints of relevant switches are verified after obtaining the reconfiguration scheme. If the constraints are not satisfied, re-perform the time period reduction and solve the reconfiguration model. This increases the amount of computation in the model solution process. To avoid this situation, the branch coding strategy based on time period reduction proposed in this paper marks the number of remote control switches and the switching times in the coding stage. And the constraints are checked at the coding stage before solving the reconfiguration model. Therefore, the computational complexity of solving the model is reduced greatly.

C. RADIATION CHECK STRATEGY

Considering that the radiative structure of the distribution network under normal operation is similar to the tree structure, therefore, the tree coding method is used to verify the radiation of the distribution network. The schematic diagram of tree coding is shown in Fig. 2. In the tree coding method, the radiation of the network will be guaranteed if all nodes appear only once. However, in this paper, the decimal coding method is used to solve the intra-day dynamic reconfiguration optimization model. Therefore, the conversion between decimal coding and the tree coding is needed to check the radiation constraints of distribution network.

The node-branch matrix and the binary node association matrix are used in the conversion between decimal coding and the tree structure coding. At first, the node-branch matrix of the current network topology is formed according to the decimal code, where each row corresponds to a branch and records the start and terminal node of the branch. Secondly, the binary node association matrix is formed according to the node-branch matrix. Finally, the tree coding matrix is formed

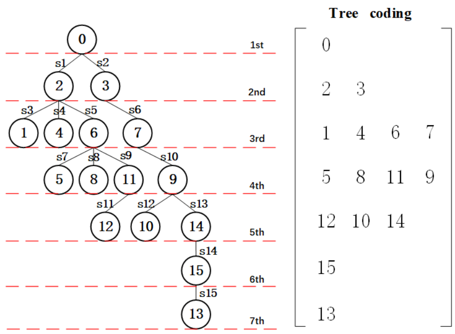

FIGURE 2. Tree coding schematic diagram.

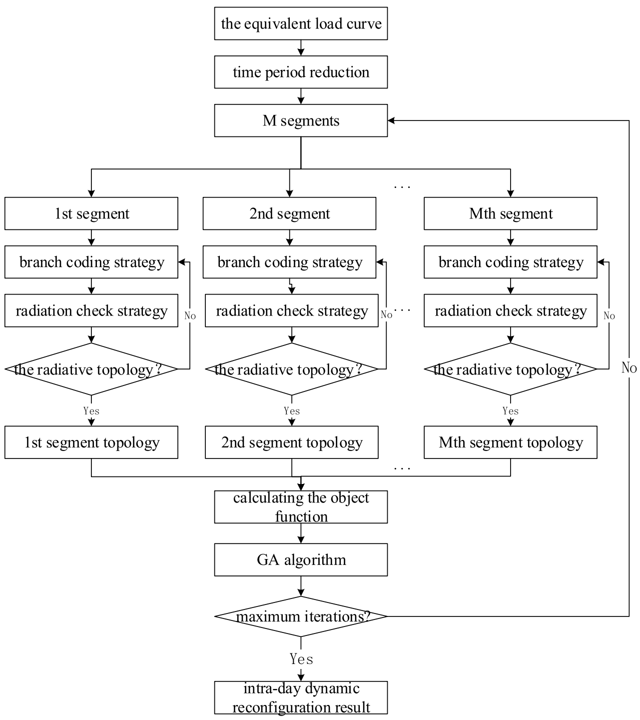

FIGURE 3. The process of model solving.

according to the node association matrix. The radiation check steps are as follows:

1. Starting from the row of the root node in the node association matrix, all the nodes connected to the root node are searched as the second layer nodes;
2. All nodes in the second layer are searched for the connected sub-nodes as the third layer nodes, and the searched nodes are not presented in the upper layer nodes;
3. Search nodes layer by layer according to step 2 until all nodes are searched. Obtain the tree structure matrix.
4. If all the nodes appear only once, the network structure is radial. If there is a node dose not be appeared or appeared at least twice, the loop or island has existed in the network.

D. THE PROCESS OF MODEL SOLVING

The process of model solving is illustrated by Fig. 3, and is explained in the following paragraphs.

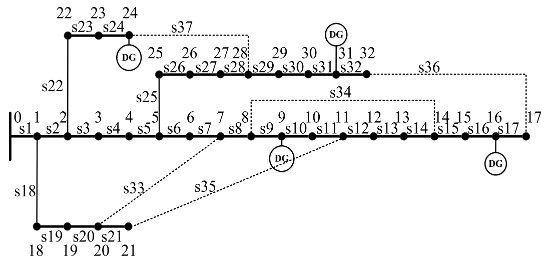

FIGURE 4. IEEE33 node distribution system with DG.

1. The 24-hour periods are divided into M segments using the time period reduction strategy based on the equivalent load curve.
2. Select 5 switches that need to be disconnected for each segment, and use the branch coding strategy based on time period reduction to generate the network topology of each segment.
3. The radiation check strategy is used to test the network topology in each segment. The topology which does not conform to the radiative topology is regenerated, and then tested until the test is satisfied.
4. The object function is calculated according to the topologies in the segments, and the result is tested by the constraints.
5. Repeat steps 2, 3, 4, and use genetic algorithm for optimization iteration.

IV. CASE STUDY

A. EXPERIMENTAL PARAMETERS

In this paper, the IEEE33 node distribution system is used to test the proposed intra-day dynamic optimization reconfiguration model, as shown in Fig. 4. The data of IEEE33 node system is referred to [29]. The rated voltage of the system is 12.66kV, the minimum and the maximum voltage limits are 0.95p.u. and 1.05p.u. respectively. The unit reactance of line is 0.4 Ω/km. The length of line in the system can be obtained by the reactance of the line. The unit fault rate is 0.065 per kilometer. The upper limit of branch current is 380A. The maximum number of remote control switches N_{RCS} is 15. The upper limit of the number of intra-day operations for a single remote switch N_{max} is 3. The upper limit of the total number of intra-day operations for all remote switches $N_{totalmax}$ is 30. Four DGs are integrated into the network at nodes 9, 16, 24, and 31 respectively. The parameters of DGs are shown in Table 1. The parameters of DGs and the data of environment are referred to [30]. The data of load in one day is referred to [31], and the uncertainty of load in the system is neglected. As in [12], the deviation between the actual and the predicted values of DG is set as 20%, and the corresponding confidence level α is 95%. In the random sampling process of probabilistic analysis, the confidence level β is 95%. The genetic algorithm is used to solve the intra-day dynamic reconfiguration model in MATLAB [32].

TABLE 1. The access node, type, power and power factor of DG.

Node	Type	Power/kW	Power Factor
9	WT	900	0.9
16	PV	600	1
24	WT	900	0.9
31	PV	600	1

TABLE 2. The loops in IEEE33 node system.

Loop	Switches in the loop	The number of switches
1	s3, s4, s5, s22, s23, s24, s25, s26, s27, s28, s37	11
2	s2, s3, s4, s5, s6, s7, s18, s19, s20, s33	10
3	s8, s9, s10, s11, s21, s33, s35	7
4	s6, s7, s8, s15, s16, s17, s25, s26, s27, s28, s29, s30, s31, s32, s36	15
5	s9, s10, s11, s12, s13, s14, s34	7

TABLE 3. The comparison of the decimal coding method and the binary coding method.

Type	Calculation of the order of magnitude	Order of magnitude
Decimal	11*10*7*15*7	80850
Binary	2^{37}	$1.37*10^{11}$

TABLE 4. The operation results in 24-period reconfigurations.

Reconfiguration times	Number of switchings	Max operation number of single switch	Operation switches set
11	36	4	s7, s10, s11, s13, s14, s16, s17, s22, s23, s24, s33, s34, s35, s36, s37

B. DECIMAL CODING METHOD

In order to calculate the solution's order of magnitude using the loop-based decimal coding method, the 5 loops in the IEEE33 node system are shown in Table 2. According to the III.B, the order of magnitude is the product of the numbers of switches in the 5 loops. In order to test the effectiveness of the decimal coding method, the order of magnitude using the decimal coding method is compared with that using the binary coding method, as shown in Table 3.

It can be seen from Table 3 that the order of magnitude using the decimal coding method is evidently smaller than that using the binary coding method, which means the generation of a valid solution is more easily when using the decimal coding method and the algorithm is more effective.

C. TIME PERIOD REDUCTION

In order to test the necessity of time period reduction, the reconfiguration model is addressed in 24-hour periods using the given probabilistic analysis method. The operation results are shown in Table 4.

It can be seen from Table 4 that in the reconfiguration, 10 switches except for s33-s37 are involved. In the 24-hour periods of reconfiguration, 11 times of reconfiguration operations are needed, including 36 operation times of the switches mentioned above. Among them, the max operation number of single switch is four times in one day. It is obvious that the reconfiguration result can not meet the remote control switch constraints. Considering that frequent reconfiguration operations may lead to an increase of misoperation probability, and frequent switching operations may lead to a decrease of switches life, the number of switching operations should be limited so that the time period reduction is necessary. The switch in Table 5 is used as remote control switches set to solve the intra-day dynamic reconfiguration model.

According to the inherent similarity of load data between adjacent periods, the time periods are divided into two segments, three segments or more segments. The segmentation results under different number of segments are shown in Table 6.

In order to verify the influence of different segmentation numbers and the superiority of the probabilistic analysis method, the probabilistic analysis method and worst-case analysis method are used to solve the reconfiguration model under different number of segments. In the worst-case analysis method, the actual value of the output is considered to be 80% of the predicted value. The remote control switches involved in the dynamic reconfiguration results of the two

TABLE 5. Remote control switches set.

Switch set
s7, s10, s11, s13, s14, s16, s17, s22, s23, s24, s33, s34, s35, s36, s37

TABLE 6. Segmentation results under different segmentation numbers.

Segmentation numbers	Segmentation results
2	(1,8), (9,24)
3	(1,8), (9,21), (22,24)
4	(1,6), (7,8), (9,21), (22,24)
……	……
24	(1), (2), ……, (23), (24)

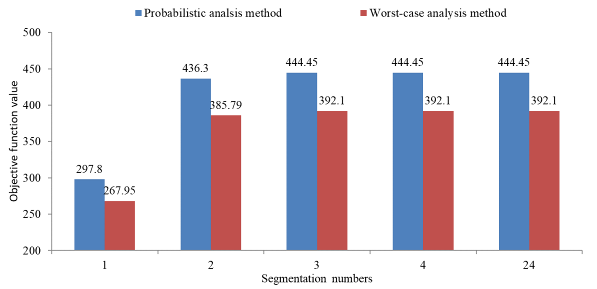

FIGURE 5. Objective function values of two models under different number of segments.

TABLE 7. Remote control switches for two models with different number of segments.

Segment	Probabilistic analysis	Worst-case analysis
1	s7,s13,s23,s35,s36	s13,s24,s33,s35,s36
2	s7,s13,s17,s22,s24,s33,s34,s35,s36	s7,s13,s17,s22,s24,s33,s34,s35,s36
3	s7,s11,s13,s22,s24,s33,s34,s35,s36	s7,s11,s13,s14,s17,s22,s24,s33,s34,s35,s36
4	s7,s11,s13,s22,s24,s33,s34,s35,s36	s7,s11,s13,s14,s17,s22,s24,s33,s34,s35,s36

TABLE 8. Calculation results with different prediction errors.

Prediction error	Operation switches	Switching times	Accommodation revenue/$	Operation cost/$	Comparison of calculation results		
10%	s7,s13,s14,s16,s22,s24,s33,s34,s35,s36	14	6486.18	912.70	Switching times	Accommodation revenue/$	Operatio n cost/$
5%	s7,s11,s14,s22,s24,s33,s34,s35,s36	14	6226.47	963.66	Probabilistic analysis		
0%	s7,s11,s14,s16,s22,s24,s33,s34,s35,s36	14	6144.10	970.83	14	6312.23	927.52
-5%	s7,s11,s14,s22,s24,s33,s34,s35,s36	14	6123.05	988.15	Worst-case analysis		
-10%	s7,s11,s13,s14,s22,s24,s33,s34,s35,s36	14	6027.10	1002.71	14	5750.62	1016.69

methods under different segmentation numbers are shown in Table 7. The optimal values of the objective functions are compared as shown in Fig. 5.

It can be seen from Fig. 5 and Table 7 that, first of all, with the increase of the segments number, the objective function values of probabilistic analysis and worst-case analysis are gradually increased, and the objective function value using probabilistic analysis method is higher than that using worst-case analysis method by 13%, which means that the probabilistic analysis method is superior to the worst-case analysis method. Secondly, because only the worst case is considered in the worst-case analysis method, the number of remote control switches participated in intra-day dynamic reconfiguration is relatively large, which has a more adverse effect on the economy due to the deployment of remote control switches. Thirdly, in the process of increasing the number of segments, the increase of the objective function value between adjacent cases is decreasing, and when the number of segments is 3 or more, the increase of the objective function is not obvious. It can be concluded that the optimal number of time-period segments is 3 in the intra-day dynamic reconfiguration in this paper.

D. ECONOMY AND ROBUSTNESS OF PROBABILISTIC ANALYSIS MODEL

In order to discuss the economy and robustness of the probabilistic analysis model, the intra-day dynamic reconfigurations under the different prediction errors (10%, 5%, 0%, −5%, −10%) between the actual output value and the predicted output value of DGs are performed. Under the 3 segments of time periods, the switching operation times, the accommodation revenue and the operation cost are compared with the results of the probabilistic analysis method and the worst-case analysis method, as shown in Table 8.

The differences of operation cost and accommodation revenue between the two methods' scheme and the optimal scheme under the given prediction error scenarios are shown in Fig. 6.

From the calculation results in Table 8, it can be seen that with the prediction error varying from 10% to -10%, the accommodation revenue of the optimal scheme is decreasing gradually, and the operating cost is increasing gradually. Although the result of probabilistic analysis method is inferior to the result of the optimal schedule under the 10% prediction error, the result of probabilistic analysis method is superior to the result under the most scenarios. It can be seen

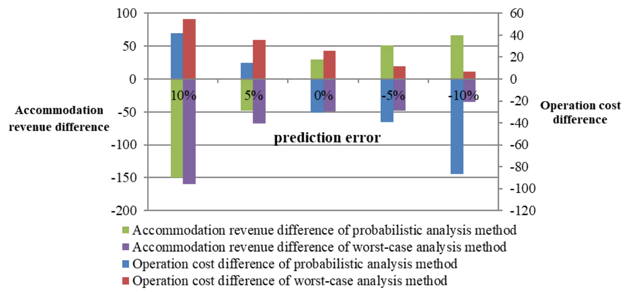

FIGURE 6. The difference values of accommodation revenue and operation cost under different prediction errors.

from Fig. 6 that the average difference of results between the probabilistic analysis method's scheme and optimal scheme under the given prediction error scenarios is lower than that between the worst-case analysis method's scheme and optimal scheme, which means that the probabilistic analysis method has better economy and robustness.

E. DISCUSSION

In the case of the same segmentation number, the operation cost and accommodation revenue of probabilistic analysis method are better than that of the worst-case analysis method. In different prediction error scenarios, the objective function values are different to some extent. On the one hand, when the actual output value of DG is high, the accommodation of DG is also higher under the branch power constraint, which leads to an increase of the accommodation revenue. On the other hand, when the accommodation of DG is high, the loads are supplied by DGs around them, and the power flowed on the other branches is smaller, so the network losses are lower, which leads to an decrease of operation cost.

However, in the worst-case analysis method, the lower bound of the DG output estimate in each period is used in the intra-day dynamic reconfiguration model to solve the problem. Although it ensures the feasibility of the reconfiguration scheme in the worst case of prediction error, the scheme will be too conservative. It can be seen from Table 8 that the scheme obtained by the worst-case analysis method has the lowest revenue and the highest operation cost. The probability that all DG's outputs are simultaneously at the lower bound of prediction is very small, so the worst-case analysis method is too pessimistic and has no validity.

The probabilistic analysis method fully takes into account the volatility of the actual value of DG near the predicted value when solving the model. As shown in Fig. 6, in five kinds of prediction error scenarios, the differences of accommodation revenue and operation cost of probabilistic analysis method show ''small fluctuations in the middle, large fluctuations on both sides and average differences of five scenarios is nearing zero'', which illustrates that the scheme obtained by the probabilistic analysis method has a larger adaptability for various kinds of prediction error. This shows the elasticity of the probabilistic analysis method.

V. CONCLUSION

In this paper, an intra-day dynamic optimal reconfiguration model based on probabilistic analysis considering both the accommodation revenue of DG and the operation cost is established. In addition to the traditional constraints, the remote control switches' number and operation times are taken as constraints. In order to obtain the optimal solution and reduce the computational complexity, this paper proposes time period reduction strategy, decimal coding strategy based on the time period reduction, and radiation check strategy using tree structure code. Finally, through the case study, we can get the following conclusions:

1. The loop-based decimal coding method is more effective than the binary coding method when generating a valid solution.
2. The number of switching and the number of remote control switches can be decreased effectively by using the time period reduction.
3. Under various given prediction errors, probabilistic analysis method has a larger adaptability and more profits than worst-case analysis, which shows that the probabilistic analysis method has good elasticity and economy.

The future work can be concentrated on the probability model of DG and load, which can make the result more accurate. The intelligent algorithm is needed to study so that the model can be solved faster.

REFERENCES

[1] H. Liu, K. Huang, N. Wang, J. Qi, Q. Wu, S. Ma, and C. Li, ''Optimal dispatch for participation of electric vehicles in frequency regulation based on area control error and area regulation requirement,'' *Appl. Energy*, vol. 240, pp. 46–55, Apr. 2019.

[2] H. Liu, J. Qi, J. Wang, P. Li, C. Li, and H. Wei, ''EV Dispatch control for supplementary frequency regulation considering the expectation of EV owners,'' *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3763–3772, Jul. 2018.

[3] J. Ouyang, M. Li, Y. Diao, T. Tang, and Q. Xie, ''Active control method of large-scale wind integrated power system with enhanced reactive power support for wind speed fluctuation,'' *IET Gener., Transmiss. Distrib.*, vol. 12, no. 21, pp. 5664–5671, Nov. 2018.

[4] J. Li, H. Zhou, E. Zhou, J. Xue, Z. Liu, and X. Wang, ''Comprehensive evaluation of impacts of high penetration distributed generation integration in distribution network,'' presented at the EI2, Nov. 2017. [Online]. Available: https://ieeexplore.ieee.org/document/8245231

[5] S. F. Santos, D. Z. Fitiwi, M. R. M. Cruz, C. M. P. Cabrita, and J. P. S. Catalão, ''Impacts of optimal energy storage deployment and network reconfiguration on renewable integration level in distribution systems,'' *Appl. Energy*, vol. 185, pp. 44–55, Jan. 2017.

[6] O. Badran, H. Mokhlis, S. Mekhilef, W. Dahalan, and J. Jallad, ''Minimum switching losses for solving distribution NR problem with distributed generation,'' *IET Gener., Transmiss. Distrib.*, vol. 12, no. 8, pp. 1790–1801, Apr. 2018.

[7] A. Ameli, A. Ahmadifar, M.-H. Shariatkhah, and M. Vakilian, ''A dynamic method for feeder reconfiguration and capacitor switching in smart distribution systems,'' *Int. J. Elect. Power Energy Syst.*, vol. 85, pp. 200–211, Feb. 2017.

[8] P. C. Ramaswamy, P. Vingerhoets, and G. Deconinck, ''Reconfiguring distribution grids for more integration of distributed generation,'' presented at the CIRED, Jun. 2013. [Online]. Available: https://ieeexplore.ieee.org/document/6683316

[9] F. Capitanescu, L. F. Ochoa, H. Margossian, and N. D. Hatziargyriou, ''Assessing the potential of network reconfiguration to improve distributed generation hosting capacity in active distribution systems,'' *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 346–356, Jan. 2015.

[10] A. Ehsan and Q. Yang, ''State-of-the-art techniques for modelling of uncertainties in active distribution network planning: A review,'' *Appl. Energy*, vol. 239, pp. 1509–1523, Apr. 2019.

[11] H. Haghighat and B. Zeng, ''Distribution system reconfiguration under uncertain load and renewable generation,'' *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2666–2675, Jul. 2016.

[12] S. Lei, Y. Hou, F. Qiu, and J. Yan, ''Identification of critical switches for integrating renewable distributed generation by dynamic network reconfiguration,'' *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 420–432, Jan. 2017.

[13] N. V. Kovački, P. M. Vidović, and A. T. Sarić, ''Scalable algorithm for the dynamic reconfiguration of the distribution network using the Lagrange relaxation approach,'' *Int. J. Elect. Power Energy Syst.*, vol. 94, pp. 188–202, Jan. 2018.

[14] K. Rahmani, F. Kavousifard, and A. Abbasi, ''Consideration effect of wind farms on the network reconfiguration in the distribution systems in an uncertain environment,'' *J. Exp. Theor. Artif. Intell.*, vol. 29, no. 5, pp. 995–1009, Jan. 2017.

[15] A. Zidan and E. F. Ei-Saadany, ''Distribution system reconfiguration for energy loss reduction considering the variability of load and local renewable generation,'' *Energy*, vol. 59, pp. 698–707, Sep. 2013.

[16] M. Rahmani-Andebili, ''Dynamic and adaptive reconfiguration of electrical distribution system including renewables applying stochastic model predictive control,'' *IET Gener., Transmiss. Distrib.*, vol. 11, no. 16, pp. 3912–3921, Nov. 2017.

[17] N. C. Koutsoukis, D. O. Siagkas, P. S. Georgilakis, and N. D. Hatziargyriou, ''Online reconfiguration of active distribution networks for maximum integration of distributed generation,'' *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 437–448, Apr. 2017.

[18] A. E. Milani and M. R. Haghifam, ''A new probabilistic approach for distribution network reconfiguration: Applicability to real networks,'' *Math. Comput. Model.*, vol. 57, nos. 1–2, pp. 169–179, Jan. 2013.

[19] Z. Li, S. Jazebi, and F. de León, ''Determination of the optimal switching frequency for distribution system reconfiguration,'' *IEEE Trans. Power Del.*, vol. 32, no. 4, pp. 2060–2069, Aug. 2017.

[20] S. Ray, A. Bhattacharya, and S. Bhattacharjee, ''Optimal allocation of distributed generation and remote control switches for reliability enhancement of a radial distribution system using oppositional differential search algorithm,'' *J. Eng.*, vol. 2015, no. 8, pp. 261–275, Jul. 2015.

[21] K. N. Miu, H.-D. Chiang, and G. Darling, ''Capacitor placement, replacement and control in large-scale distribution systems by a GA-based two-stage algorithm,'' *IEEE Trans. Power Syst.*, vol. 12, no. 3, pp. 1160–1166, Aug. 1997.

[22] Q. Zhou, D. Shirmohammadi, and W.-H. E. Liu, ''Distribution feeder reconfiguration for operation cost reduction,'' *IEEE Trans. Power Syst.*, vol. 12, no. 2, pp. 730–735, May 1997.

[23] E. A. Bueno, C. Lyra, and C. Cavellucci, ''Distribution network reconfiguration for loss reduction with variable demands,'' in *Proc. IEEE/PES T&D*, Nov. 2004, pp. 384–389.

[24] R. A. Jabr, ''Minimum loss operation of distribution networks with photovoltaic generation,'' *IET Renew. Power Gener.*, vol. 8, no. 1, pp. 33–44, Jan. 2014.

[25] A. M. Tahboub, V. R. Pandi, and H. H. Zeineldin, ''Distribution system reconfiguration for annual energy loss reduction considering variable distributed generation profiles,'' *IEEE Trans. Power Del.*, vol. 30, no. 4, pp. 1677–1685, Aug. 2015.

[26] C.-B. Hou and R.-F. Wang, ''Dynamic reconfiguration of distribution network with distributed generation based on clustering,'' *Int. J. Elect. Eng.*, vol. 24, no. 2, pp. 71–79, Apr. 2017.

[27] H. Fathabadi, "Power distribution network reconfiguration for power loss minimization using novel dynamic fuzzy c-means (dFCM) clustering based ANN approach," *Int. J. Elect. Power Energy Syst.*, vol. 78, pp. 96–107, Jun. 2016.
[28] Y.-Y. Fu and H.-D. Chiang, "Toward optimal multiperiod network reconfiguration for increasing the hosting capacity of distribution networks," *IEEE Trans. Power Del.*, vol. 33, no. 5, pp. 2294–2304, Oct. 2018.
[29] V. A. Evangelopoulos and P. S. Georgilakis, "Optimal distributed generation placement under uncertainties based on point estimate method embedded genetic algorithm," *IET Gener. Transmiss. Distrib.*, vol. 8, no. 3, pp. 389–400, Mar. 2014.
[30] Z. Liu, Y. Chen, R. Zhuo, and H. Jia, "Energy storage capacity optimization for autonomy microgrid considering CHP and EV scheduling," *Appl. Energy*, vol. 210, pp. 1113–1125, Jan. 2018.
[31] Y. Huping, P. Yunyan, and X. Ning, "A static method for distribution network dynamic reconfiguration," *Power Syst. Protection Control*, vol. 37, no. 8, pp. 53–57, Apr. 2009.
[32] A. G. Patel and C. Patel, "Distribution network reconfiguration for loss reduction," presented at the ICEEOT, Mar. 2016. [Online]. Available: https://ieeexplore.ieee.org/document/7755453

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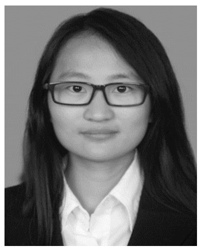

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