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Multi-period Robust Dispatch of Active Distribution Network Based on Scene Analysis Method

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Abstract. With the large-scale access of intermittent renewable energy, the active distribution networks (ADN) is facing great challenges on achieving full consumption and efficient use of intermittent renewable energy on the premise of ensuring safe operation. To resolve these issues, a novel multi-period robust dispatch strategy for ADN based on scene analysis method is proposed in this paper. Then, the second-order cone relaxation (SOCR) is used to transform the original model into a mixed integer second-order cone programming (SOCP), which gains as much improvement as possible in computational performance at the expense of as few losses as possible in accuracy. Finally, numerical test on the modified IEEE 33-bus test system demonstrates that on the premise of realizing the maximum utilization of DG, the proposed strategy can also achieve the purposes of energy-saving, loss reduction and improvement in voltage level.

1. Introduction

With the increasing penetration of such as WT, PV, etc., the traditional distribution networks are gradually becoming ADN including many controllable resources [1-2]. However, the uncertainty of WT and PV brings a new and major challenge to the safe operation and coordinated dispatch of power systems [3-6]. The grid-connected DG with high-permeability can cause voltage fluctuations, overvoltage, power blocking, even off-grid, which seriously restrict ADN's ability to absorb renewable energy generation. Therefore, there is an urgent need to find core technologies that can better solve these problems. ADN's multi-period optimization, arranging the dispatch plan of each device from a forward-looking perspective, is an effective way to solve such problems.

Nowadays, in response to ADN optimization dispatch, many scholars have carried out some research and accumulated some academic achievements. Meanwhile, due to the shortcomings of heuristic intelligent algorithm that global optimization cannot be guaranteed and solution speed is relatively slow, seeking quick and efficient numerical optimization method to solve the optimal power flow (OPF) problems are attracting significant attention[5-10]. In response to this demand, based on the SOCR technology, the literature [5-6] first systematically established a branch flow model (BFM) framework based on Distflow to solve the OPF and proposed a two-step relaxation step. Meanwhile, the literature [5-6] also proved the relaxation accuracy. The literature [7] established a two-stage robust reactive power optimization model based on BFM. Meanwhile, the optimization model was transformed into mixed integer SOCP by using SOCR. In [8], based on the operating characteristics of radial distribution network, a three-phase reactive power optimization model based on BFM is



established and the optimization model is also transformed into SOCP by SOCR. In [9], the active-reactive coordination optimization model of radial distribution network is proposed and the reasonable plans for DG, ESS and CB in ADN are arranged. Based on the SOCR technology, the literature [10] establishes the dynamic OPF framework for distribution network, and validates the effectiveness of this framework.

To the best of our knowledge, in the above research, there are mainly the following issues: 1) the multiple uncertainties of source-load are not taken into account. At present, the prediction accuracy of WT, PV and load is not ideal in the distribution network, so the uncertainty of source-load will be processed more realistically in the day-ahead dispatch stage. 2) The coordinated operation of active-reactive power and multiple adjustable resources is not considered. Due to the strong coupling of active-reactive power in the distribution network [9], it is not reasonable to analyse the distribution network according to the traditional active/reactive decoupling theory [11]. Meanwhile, the coordinated operation of multiple resources with different operating characteristics will be more conducive to the safe and efficient operation of system. 3) The reactive power output of WT and PV is not used as the control variable for coordinated dispatch and the inverters can provide reactive power support based on the active-reactive decoupling control strategy, which will be a new effective solution to solve the consumption problem of intermittent renewable energy.

Aiming at the issues in the above research, based on the existing research theories, this paper proposes a multi-period robust dispatch strategy based on scene analysis method for active distribution network. By screening typical scenarios, the ADN optimization dispatch schemes under severe scenarios are obtained. It improves the safety of system operation, and realizes the full consumption and efficient use of renewable clean energy. At the same time, the original model is convexized and relaxed by the second-order cone relaxation technique, which better balances the solution accuracy and the solution efficiency.

2. Active-reactive Power Coordination Dynamic Optimization Mathematical Model

2.1 Source-load uncertainty modelling

Due to the strong randomness and volatility of DG and load, this paper deals with source-load uncertainty by the probabilistic scenario method, which will further improve the proposed model practical. In this paper, the prediction error of load and PV adopts the probability density function obeying the normal distribution [12]. Due to the predicted output error of WT with a large kurtosis and skewness, to better reflect the error distribution characteristics of WT, this paper uses Beta distribution to describe its prediction error, and corresponding probability density function is referred to [13].

2.1.1 Probability Scene Generation of Source-Load. Since the multi-dimensional randomness of WT, PV and load needs to be described when the source-load probability scene is generated, this paper uses multi-dimensional sampling theory to perform multi-dimensional layered sampling. Latin hypercube sampling (LHS), an ideal multi-dimensional hierarchical sampling method, is used to sample the source-load uncertainty [14]. The specific sampling method is as follows [14].

2.1.2 Scene Reduction. According to the LHS principle, the larger the sampling scale, the higher the accuracy, but the calculation efficiency is reduced. To reduce the calculating pressure and retain the characteristics of the original scene as much as possible, the similar scenes are merged by the scene reduction technique. In this paper, the simultaneous backward reduction (SBR) technology is used for scene reduction. Then the specific scene reduction method is referred to [14].

2.2 Branch Flow Form of Radial Distribution Network

2.2.1 Active/Reactive Power Flow Equation Constraint. By converting into the complex non-convex nonlinear optimization model into a cone model, the complex relationship between variables can be

represented by the cone set with special structure, which greatly simplifies the complexity of original model and speeds up its convergence [15].

For the ADN with radiant operation, this paper uses the SOCR technique to convex-relax flow equation constraints. The Distflow-branch flow form of the transformed optimization model is as follows:

$$\begin{cases} \sum_{i \in u(j)} [P_{ij}^t - r_{ij} \tilde{I}_{ij}^t] = \sum_{k \in v(j)} P_{jk}^t + P_j^t \\ \sum_{i \in u(j)} [Q_{ij}^t - x_{ij} \tilde{I}_{ij}^t] = \sum_{k \in v(j)} Q_{jk}^t + Q_j^t \\ P_j^t = P_{j,WT}^t + P_{j,PV}^t - P_{j,d}^t \\ Q_j^t = Q_{j,WT}^t + Q_{j,PV}^t + Q_{j,SVC}^t + Q_{j,CB}^t - P_{j,d}^t \end{cases} \quad (1)$$

$$\tilde{V}_j^t = \tilde{V}_i^t - 2(r_{ij} P_{ij}^t + x_{ij} Q_{ij}^t) + [(r_{ij})^2 + (x_{ij})^2] \tilde{I}_{ij}^t \quad (2)$$

$$\left\| \begin{matrix} 2P_{ij}^t \\ 2Q_{ij}^t \\ \tilde{I}_{ij}^t - \tilde{V}_{ij}^t \end{matrix} \right\|_2 \leq \tilde{I}_{ij}^t + \tilde{V}_{ij}^t \quad (3)$$

where, r_{ij} and x_{ij} denote the resistance and reactance of branch ij ; $\tilde{I}_{ij}^t$ is the current square of the branch ij ; $\tilde{V}_j^t$ is the voltage square of node j ; P_{ij}^t and Q_{ij}^t are the active and reactive power in the head of branch ij at time t ; P_j^t and Q_j^t are active and reactive power injected to node j at time t ; $P_{j,WT}^t$ and $P_{j,PV}^t$ are the active power output of WT and PV for node j ; $P_{j,d}^t$ is the active power demand of load for node j ; $Q_{j,WT}^t$, $Q_{j,PV}^t$, $Q_{j,SVC}^t$ and $Q_{j,CB}^t$ are the reactive power output of WT, PV, SVC and CB for node j at time t , respectively; $P_{j,d}^t$ is the reactive power demand of load for node j at time t .

2.2.2 System Operation Security Constraints

$$\begin{cases} V_i^{\min} \leq V_i^t \leq V_i^{\max} \\ I_{ij}^t \leq I_{ij}^{\max} \end{cases} \quad (4)$$

Where I_{ij}^t is the current amplitude of branch ij at time t ; the subscript max and min are the upper and lower limits of the corresponding variables, the following are similar; $I_{ij}^{\max}$ is the upper limit of current amplitude of branch ij .

2.2.3 Operation Constraints of CB. The action time of CB is strictly limited in a dispatch cycle due to lifetime [7]. Moreover, as discrete controllable device, each switching of CB is done in groups. Further, the operation constraints are modelled by the binary variable. The specific operational constraints are as follows:

$$\begin{cases} Q_{i,CB}^t = N_{i,CB}^t \cdot Q_{i,CB}^{step} \\ N_{i,CB}^t \leq N_{i,CB}^{\max}, \quad N_{i,CB}^t \in \text{int} \\ B_{i,CB}^t \in \{0,1\} \\ \sum_{t=1}^{T-1} B_{i,CB}^t = B_{CB}^{\lim} \end{cases} \quad (5)$$

$$B_{i,CB}^t \cdot Q_{i,CB}^{step} \leq |Q_{i,CB}^{t+1} - Q_{i,CB}^t| \leq B_{i,CB}^t \cdot N_{i,CB}^{\max} \cdot Q_{i,CB}^{step} \quad (6)$$

Where $Q_{i,CB}^{step}$ and $Q_{i,CB}^t$ are the single group compensation power and actual operating compensation power of CB connected to node i ; $N_{i,CB}^t$ is the actual operational groups of CB connected to node i ; $B_{i,CB}^t$ is a 0-1 state transition variable. $B_{i,CB}^{lim}$ is maximum allowable action time of the i -th CB in a dispatch cycle.

2.2.4 Operation Constraints of OLTC. The OLTC, as a discrete controllable device, should not be adjusted frequently due to physical limit. Hence, the action time of OLTC is strictly limited in a dispatch cycle. The specific operational constraints are as follows:

$$\begin{cases} (V_i^{min})^2 \leq (V_{i,h}^t)^2 \leq (V_i^{max})^2 \\ k_i^{min} \leq k_i^t \leq k_i^{max} \end{cases} \quad (7)$$

Where $V_{i,h}^t$ is the voltage amplitude in the high voltage side of OLTC, which is a constant value; k_i^t is the square of the OLTC's ratio, which is a discrete variable; k_i^t is modelled by means of 0-1 variable as follows:

$$k_i^t = k_i^{min} + \sum_s k_{i,s} \cdot \gamma_{j,s,t}^{OLTC} \quad (8)$$

Where $k_{i,s}$ is the difference of ratio square between the gear s and the gear $s-1$; $\gamma_{i,s,t}^{OLTC}$ is the 0-1 identification variable.

Further, the action number limit of OLTC in a dispatch period is modelled with the binary variables 0-1, and the specific operating constraints^[10] are as follows:

$$\begin{cases} \gamma_{i,SR_j,t}^{OLTC} \leq \gamma_{i,2,t}^{OLTC} \leq \gamma_{i,1,t}^{OLTC} \\ \gamma_{i,t}^{OLTC,in} + \gamma_{i,t}^{OLTC,de} \leq 1 \\ \gamma_{i,t}^{OLTC,in} - \gamma_{i,t}^{OLTC,de} \cdot N_{i,OLTC}^{max} \leq \sum_s \gamma_{i,S,t}^{OLTC} - \sum_s \gamma_{i,S,t-1}^{OLTC} \\ \sum_s \gamma_{i,S,t}^{OLTC} - \sum_s \gamma_{i,S,t-1}^{OLTC} \leq \gamma_{i,t}^{OLTC,in} \cdot N_{i,OLTC}^{max} - \gamma_{i,t}^{OLTC,de} \\ \sum_{t \in T} (\gamma_{i,t}^{OLTC,in} + \gamma_{i,t}^{OLTC,de}) \leq N_{i,OLTC}^{lim} \\ \gamma_{i,t}^{OLTC,in}, \gamma_{i,t}^{OLTC,de} \in \{0,1\} \end{cases} \quad (9)$$

Where $\gamma_{i,t}^{OLTC,in}$ and $\gamma_{i,t}^{OLTC,de}$ are the gear position change indicators of OLTC. $\gamma_{i,t}^{OLTC,in}=1$ means that the gear position of OLTC at time t is larger than the gear position at time $t-1$; $\gamma_{i,t}^{OLTC,de}=1$ means that the gear position of OLTC at time t is smaller than the gear position at time $t-1$; $N_{i,OLTC}^{max}$ is the maximum change range of gear position; $N_{i,OLTC}^{lim}$ is maximum allowable action time of OLTC in the dispatch period.

2.2.5 Operational Constraints of DG. To make full use of renewable clean energy, this paper gives priority to ensuring full consumption of WT and PV. The PV system connected to the grid through the inverter can realize the reactive power compensation while ensuring the maximum active output by the reasonable control strategy, and the reactive power limit that can be output to the system is referenced [16]. The doubly fed induction generator (DFIG) can realize de-coupled control of active-reactive power by AC-DC-AC frequency converter, so that it dynamically adjusts its reactive power output. The reactive power output limit of DFIG can be determined by between stator-side and grid-side inverters, and the reactive power output limit of WT is referred to [17].

The active operation constraints of WT and PV are as follows:

$$\begin{cases} 0 \leq P_{i,PV}^t \leq P_{i,PV}^{t,pre} \\ 0 \leq P_{i,WT}^t \leq P_{i,WT}^{t,pre} \end{cases} \quad (10)$$

Where $P_{i,PV}^{t,pre}$ and $P_{i,WT}^{t,pre}$ are the predicted power of PV and WT connected to node i at time t .

2.2.6 Operational Constraint of SVC. ADN may cause the reverse power flow in the source peak and load valley period, which leads to overvoltage problem. The traditional pure capacitive compensation method should also be adjusted in time. Hence, this paper takes SVC with broad development prospects as an adjustable resource, which can also reflect the operation characteristics of the discrete-continuous reactive power compensation devices. The operation constraints are as follows:

$$Q_{i,SVC}^{\min} \leq Q_{i,SVC}^t \leq Q_{i,SVC}^{\max} \quad (11)$$

Where $Q_{i,SVC}^t$ denotes the reactive compensation power of the SVC connected to the node i at time t .

2.2.7 Operational Constraints of Distribution Port. To reduce the impact of power fluctuations on the upper-level grid, it is necessary to control the power exchange of the distribution port within a certain range [8].

$$\begin{cases} P_g^{\min} \leq P_g^t \leq P_g^{\max} \\ Q_g^{\min} \leq Q_g^t \leq Q_g^{\max} \\ \sqrt{(P_g^t)^2 + (Q_g^t)^2} \leq S_{MTF} \end{cases} \quad (12)$$

Where P_g^t and Q_g^t are the active/reactive power injected into ADN from upper power grid at time t , respectively; S_{MTF} is the maximum load capacity limit of OLTC.

2.3 Objective Function

For the multi-period robust dispatch model of ADN based on scene analysis method, the minimum system running network loss in the dispatch period is selected as the objective function.

$$\min \sum_{t=0}^T P_{loss}^t (Q_{WT}^t, Q_{PV}^t, Q_{SVC}^t, Q_{CB}^t, k_i^t) \quad (13)$$

Where T is the total dispatch period; P_{loss}^t is the network loss in the time period t .

So far, the multi-period robust dispatch model of ADN based on scene analysis method can be described as follows:

$$\begin{cases} \min \sum_{t=0}^T f(x_t, y_t) \\ \text{s.t.} \quad \begin{aligned} &h_t(x_t, y_t) = 0 \\ &g_t(x_t, y_t) \leq 0 \\ &x_{t,\min} \leq x_t \leq x_{t,\max} \\ &y_{t,\min} \leq y_t \leq y_{t,\max} \end{aligned} \end{cases} \quad (14)$$

Where x_t is the state variable; y_t is the control variable.

The objective function and constraints of the model described by equation (14) satisfy the decision condition of convex programming, and equation (3) satisfies the definition of second-order cone, so the transformed model is a SOCP problem.

3. Robust Optimization Solution Strategy based on Scene Analysis

In order to cope with the impact of uncertainty on control decision, a more effective method is to find the worst scene from scene set, so that the decision-making scheme can still ensure the safe operation of system in the worst scene. In this paper, the worst scene is defined as the scene with the largest voltage deviation. The model can be described as follows:

$$\begin{cases} \max_d f(x, y, d) = \sum_{t \in T} \sum_{j \in \phi} |V_{j,t} - \hat{V}_j| \\ \text{s.t.} \\ g(x, y, d) = 0 \\ h(x, y, d) > 0 \\ d \in D \end{cases} \quad (15)$$

Where $g(x, y, d) = 0$ is the equality constraint; $h(x, y, d) > 0$ is the inequality constraint; $\hat{V}_j$ is the expected value of the voltage at node j , typically $\hat{V}_j = 1$.

The multi-period robust optimization strategy considering uncertainty factors and prediction errors can be split into two-layer programming problems. The outer main problem is to solve the problem that can minimize the objective function value under the given the predicted power of source-load. The inner sub-problem is to solve the worst power fluctuation scene for a given control strategy. The relationship between the two layers of optimization problems is shown in Figure 1.

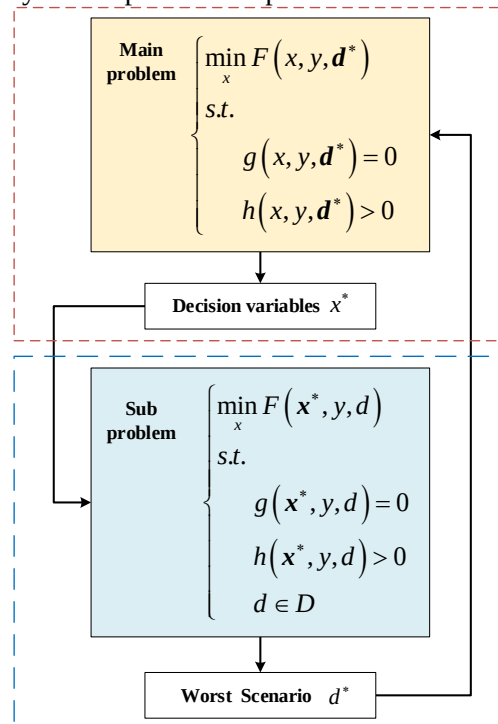


Figure 1. Robust optimization dispatch strategy considering the prediction errors of source-load

The typical scene set obtained based on scene generation and reduction can reduce the number of scenes in the case of the original scene set is sufficiently approximated, which can effectively avoid the computational burden caused by the large number of scenes.

For a single scene c_i in a typical scene set, the vector d characterizing the power fluctuations is known. Then, the two-layer robust optimization problem can be transformed into a single objective function model containing only its main problem.

$$\begin{cases} \max_x F(x, y, d_i) \\ \text{s.t.} \\ g(x, y, d_i) = 0 \\ h(x, y, d_i) > 0 \\ d_i \in c_i \end{cases} \quad (16)$$

Where d_i denotes the predicted power of WT, PV and load in scenario c_i .

The model (16) is solved by the solution method based on the SOCP, and the multi-source coordination optimization dispatch is performed based on typical scenario information. The scene with the largest voltage deviation is selected as the worst scene. The optimal solution that satisfies the system operation security requirements in the worst case scenario is the robust optimization solution. The multi-period robust dispatch solution process of ADN based on scene analysis method is shown in Figure 2.

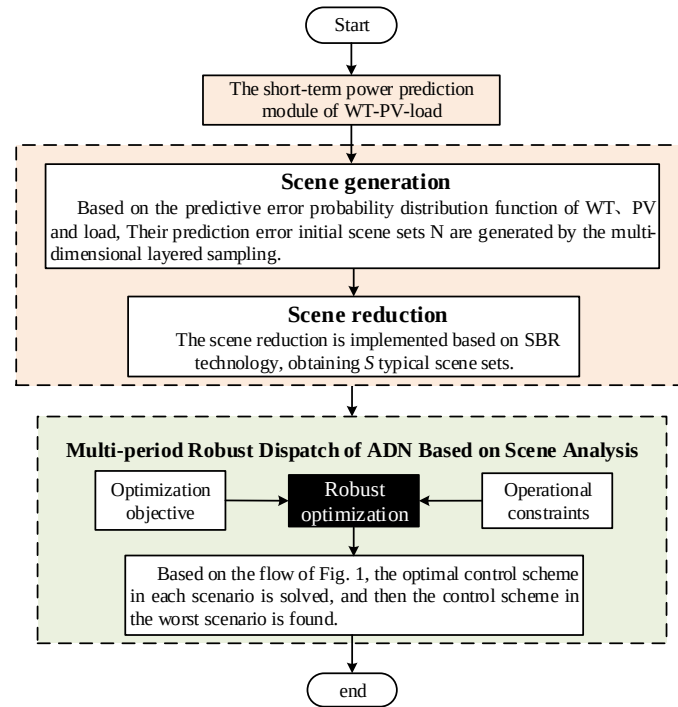


Figure 2. The robust optimization solution process based on scene analysis method

4. Simulation Analysis

4.1 Overview of Test System

In this section, the modified IEEE 33-bus test system is used to verify the practicality of the proposed dispatch strategy. Therein, the OLTC with step being 0.01 and the switchable range being [0.95, 1.05] in the substation accesses to the root node 1, and the maximum allowable action time in a dispatch cycle is 5. Two CBs with rated capacities being 0.2 Mvar and steps being 0.02 Mvar are connected to buses {#3, #9}, and the maximum allowable action time in a dispatch cycle both is 5. The DFIGs are connected to buses {#20, #25} with rated capacity being 0.3 MW. The PVs are connected to buses {#14, #28} with rated capacity being 0.2 MW. The SVC are connected to buses {#22, #31} with adjustment range being [-100-200] kvar. The specific topology of the modified IEEE 33-bus test system is shown in Figure 3. The typical scenarios of WT, PV and load are obtained based on subsection 2.1 as shown in Figure 4.

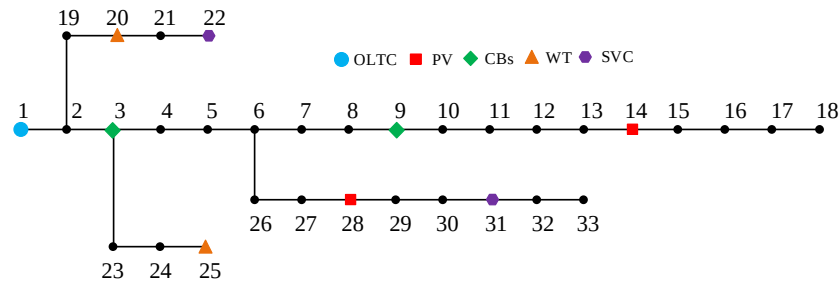


Figure 3. Diagram of modified IEEE 33-bus distribution network

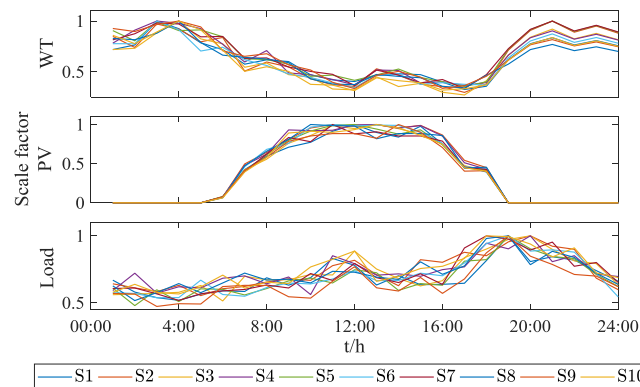


Figure 4. Forecast of Load, WT and PV for next day

4.2 Analysis of Results

Based on the information of source-load in Figure 4, the multi-period robust dispatch model of ADN based on scene analysis method is simulated. The network loss before and after optimal dispatch is shown in Figure 5; Figure 6 describes the node voltages after the optimal dispatch; Figure 7 shows the dispatch plans of adjustable resources; Figure 8 shows the switching plans of OLTC.

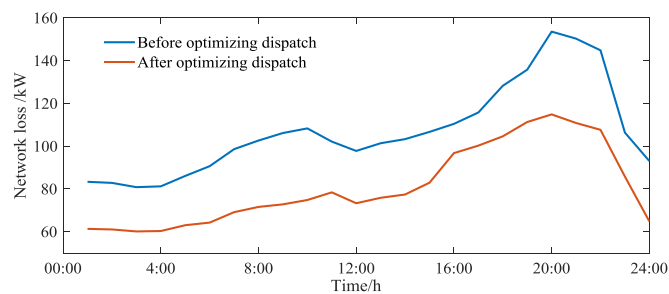


Figure 5. Comparison of network loss before and after optimization dispatch

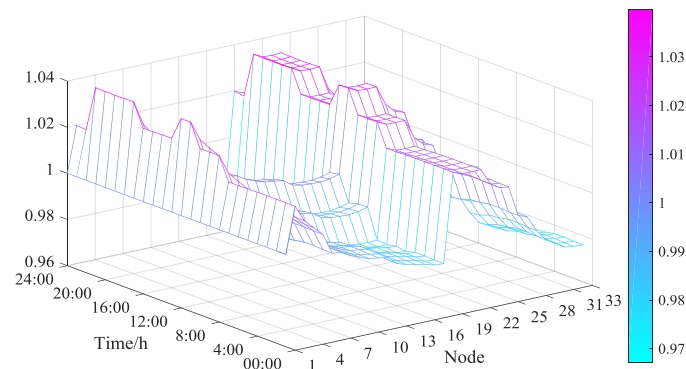


Figure 6. The node voltage of each period after optimization dispatch

It is shown in Figure 5 that the system network loss in each period has been greatly improved after optimized dispatch. In particular, the system network loss is obviously improved during the high-demand daytime hours. Meanwhile, in-depth view, the active-reactive power local compensation relieves line congestion and reduces network loss. It can be seen from Figure 6 that after the optimization dispatch, the node voltages of each period are in the $[0.95-1.05]$, which meets the voltage level requirements of distribution network. Moreover, from the Figure 8, it can be known that the switching gear of OLTC has a greater influence on the node voltage level.

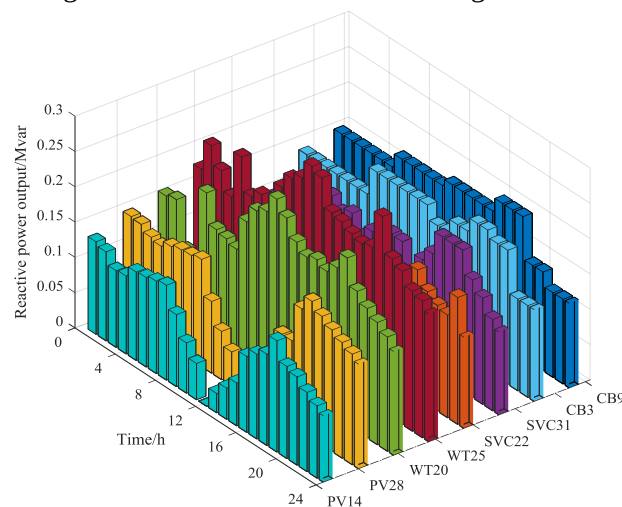


Figure 7. Dispatch strategy for each adjustable resources

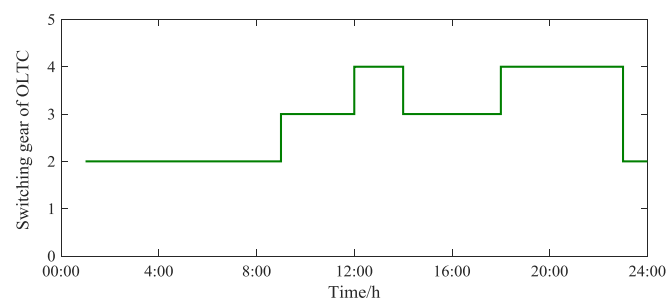


Figure 8. Switching gears for each period of OLTC

For optimal dispatch plans of WT and PV in Figure 7, we can see that the dispatch results satisfy the operational constraints of respective grid-connected inverters. For optimal dispatch plans of SVC in Figure 7, it can be continuously and quickly adjusted as the system load fluctuates. Meanwhile, its

reactive power output is related to its access location, the node 31 and its nearby nodes have relatively large reactive power requirements, and the reactive power output of the SVC31 is almost greater than the SVC22 in each period. For optimal dispatch plans of CB in Figure 7, the CB3 and CB9 all satisfy the constraints of action time, and the switching operation mostly occur when the system payload fluctuates greatly.

From Figure 8, the OLTC switching plans also satisfies the constraints of its action time, and the switching gear is approximately consistent with load demand. In addition, during whole dispatch period, the OLTC is always in positive adjustment, which is related to the voltage at the end of feeder is far from the acceptable level [18]. However, it can be foreseen that with the continuous improvement of DG penetration rate, the node voltage at the end of feeder will gradually increase and the OLTC will have a negative adjustment to solve overvoltage problem.

5. Conclusion

Aiming at the problem of coordinated operation of multiple adjustable resources, full consumption and efficient use of intermittent renewable energy on the premise of ensuring safe operation. This paper proposes a novel multi-period robust dispatch strategy for ADN based on scene analysis method to develop a reasonable and efficient operation strategy for multiple adjustable resources under the premise of ensuring safe operation. The work in this paper shows that:

- 1) The proposed multi-period robust dispatch strategy based on scene analysis can better achieve full consumption and efficient use of intermittent renewable energy on the premise of ensuring safe operation. Meanwhile, this strategy can also reduce system operating network loss and improve voltage levels.
- 2) The second-order cone relaxation is used to transform the original model into a mixed integer second-order cone programming, which gains as much improvement as possible in computational performance at the expense of as few losses as possible in accuracy.

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