Security-constrained Transmission Maintenance Optimization Considering Generation and Operational Risk Costs

Dan Xu, Zhi Cai, Qian Cheng, Guodong Huang, Jingyang Zhou, and Junjie Tang

***Abstract*—With the large-scale integration of renewable energy, the traditional maintenance arrangement during the load valley period cannot satisfy the transmission demand of renewable energy generation. Simultaneously, in a market-oriented operation mode, the power dispatching control center aims to reduce the overall power purchase cost while ensuring the security of the power system. Therefore, a security-constrained transmission maintenance optimization model considering generation and operational risk costs is proposed herein. This model is built on double-layer optimization framework, where the upper-layer model is used for maintenance and generation planning, and the lower-layer model is primarily used to address the operational security risk arising from the random prediction error and $N-1$ transmission failure. Correspondingly, a generation-maintenance iterative algorithm based on a defined cost feedback is included to increase solution efficiency. Generation cost is determined using long-term security-constrained unit commitment, and the operational risk cost is obtained using a double-layer $N-1$ risk assessment model. An electrical correlation coupling coefficient is proposed for the solution process to avoid maintenance of associated equipment simultaneously, thereby improving model convergence efficiency. The IEEE 118-bus system is used as a test case for illustration, and test results suggest that the proposed model and algorithm can reduce the total cost of transmission maintenance and system operation while effectively improving the solution efficiency of the joint optimization model.**

***Index Terms*—Transmission maintenance, security-constrained unit commitment, iterative algorithm, cost feedback, $N-1$ risk assessment.**

NOMENCLATURE

$\gamma_{k,d}$	Resources consumed by equipment k for maintenance on day d
$\delta_{l_d,t}$	Compensation price of load l_d shedding during period t
Δp_a^b	Active power transferred to equipment a
$\Delta p_{l_d,t}$	Cutoff power of load l_d during period t
$\boldsymbol{\theta}$	Node phase angle vector
$\theta_{bh,t}$, $\theta_{bt,t}$	Phase angles of head and end nodes of branch b during period t
$\boldsymbol{\lambda}$	Dual variable of original subproblem
φ	A determined boundary parameter
$\psi_{d\text{-}n}$	Maintenance operation cost of simultaneous maintenance of n equipment on day d
$b \in E$	Branch composition of Section E
$B_{i,on}$	The minimum start-up time requirement of unit i
$B_{i,off}$	The minimum shut-down time requirement of unit i
$B_{i,t}^{on}$, $B_{i,t}^{off}$	Start-up and shut-down times of unit i
$c_{k,d}$	Maintenance cost of equipment k on day d
$\boldsymbol{d}$	Value coefficient
d_0, d_1	Starting and end days when equipment k is in maintenance state
D	Total number of days
D_{ab}	Electrical correlation coupling coefficient of equipment a and equipment b
$D_{a\text{-}b}$	Power flow transfer coefficient of equipment b to equipment a after equipment b is tripped
$\boldsymbol{E}$	Constraint coefficient matrix
f_1	Generation cost
f_2	Maintenance cost
f_3	Operational risk cost
f_4	Desired improvement in transmission and transformation maintenance scheduling (TTMS) optimization objective transformed from f_2
f_5	Improvement in maintenance optimization objective adjusted from f_4
$F(p_{i,t})$	Operation cost of unit i during period t
J_k, $J_{k'}$	Durations of equipment k and k'
K	Total number of maintenance equipment
$l_{b,t}$	Power flow of branch b during period t

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D. Xu, Z. Cai, G. Huang, and J. Zhou are with Beijing Key Laboratory of Research and System Evaluation of Power Dispatching Automation Technology, China Electric Power Research Institute, Beijing 100192, China (e-mail: xudan@epri.sgcc.com.cn; caizhi@epri.sgcc.com.cn; huangguodong@epri.sgcc.com.cn; zhoujingyang@epri.sgcc.com.cn).

Q. Cheng and J. Tang (corresponding author) are with State Key Laboratory of Power Transmission Equipment & System Security and New Technology, Chongqing University, Chongqing 400044, China (e-mail: qiancheng98@cqu.edu.cn; tangjunjie@cqu.edu.cn).

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$l_{b,\max}$	Upper limit of thermal stability of branch b
L_d	Total number of loads
$M_{E,t}$	Active power flow of transmission Section E during period t
$M_{E,t,\max}$	Limit of Section E during period t
$M_{E,1}$, $M_{E,2}$, $M_{E,3}$	Limits of Section E when section members are not maintained and when one member is maintained
N	Total number of units
$\boldsymbol{p}$	Node injection power vector
p_b	Active power of equipment b before fault
$P_{d,t}$	Negative reserve demand of system
$p_{i,\max}$	The maximum output of unit i
$p_{i,\min}$	The minimum output of unit i
$p_{i,up}$, $p_{i,down}$	Upper and lower limits of unit i ramp
$p_{l_d,t}$	Demand of load l_d during period t
$P_{T,t}$	Power transmission and receiving plan of system during period t with positive receiving and negative transmission
$P_{u,t}$	Positive reserve demand of system
$p_{v_1\text{-}v_2}$	Penalty cost for simultaneous maintenance of equipment v_1 and equipment v_2
$r_{\Phi,d}$	Generation cost considering equipment maintenance set $\Phi_d=\{S_{1,d}^m, S_{k,d}^m, \ldots, S_{K,d}^m\}$ on day d
$r'_{\Phi,d}$	Increased generation cost considering equipment maintenance set Φ_d on day d
r_d	Generation cost without considering any maintenance on day d
$r'_{i_1\text{-}i_2,d}$	Maintenance operation cost of sum of maintenance costs of equipment i_1 and equipment i_2 on day d compared with sum of maintenance costs of i_1 and i_2
$r'_{k-1,d}$	Single-equipment maintenance cost of equipment k on day d
R_d	Total resources that can be provided on day d
$S_{f,b}$	Indicator of fault state of equipment b
$S_{i,t}^s$	State of unit i during period t
$S_{k,d}^m$, $S_{k',d}^m$	States of equipment k and k' to be maintained on day d
$S_{N,i}$	The maximum number of times unit i begins up and shuts down
Tp	Total generation scheduling period
$U(p_{i,t})$	Start-up cost of unit i during period t
$\boldsymbol{x}$	Set of decision variables
x_b	Reactance of branch b
$z_{a\text{-}b}$	Mutual impedance between two equipment port nodes
$z_{b\text{-}b}$	Self-impedance of open port
$\boldsymbol{Z}$	Impedance matrix vector

I. Introduction

THE primary task of maintenance scheduling (MS) is to reasonably arrange the combination of maintenance and the outage periods of generation, transmission, and transformation equipment, to guarantee the operational security and cost-effectiveness of the power system. In China, the Electric Power Dispatching Control Center has typically arranged equipment maintenance scheduling in spring and autumn (two load valleys during one year), followed by generation scheduling (GS) based on the boundary conditions which are determined from MS. However, decoupling MS and GS may lead to the operational efficiency reduction and potential risk increase. Transmission and transformation maintenance scheduling (TTMS) reduces the transmission capacity of the power system, resulting in several issues: an increased risk of load shedding, the need for GS adjustments and additional generation costs (GCs), and the possibility of curtailing renewable energy due to transmission limitations. Therefore, it is necessary to study the combined optimization model and method of GS and MS considering the operational economy and risk.

Existing research on MS can be broadly categorized into equipment noumenon maintenance (e. g., condition maintenance based on the evaluation of each single equipment condition in practical operation [1], [2]) and optimal arrangement of maintenance from a systematic viewpoint. Unit maintenance primarily affects the available generation capacity of the entire system, while transmission maintenance leads to a topology change in the power system; thus, they can be studied separately [3], [4]. TTMS affects the power system topology, reduces the power transmission capacity of the power system, and changes the operation mode of the entire system. Therefore, a common maintenance modeling concept is to build a maintenance optimization model by taking the minimum maintenance cost (MC) and the risk loss of power system outage as the optimization objective, and taking the maintenance duration and system operation security as the constraints [5]-[7]. When the network topology changes, it is difficult to accurately consider the power flow distribution and transmission capacity change in the TTMS optimization model. However, an optimization model of TTMS that considers changes in network topology is proposed [8]. Although the proposed model and method can reduce wind curtailment by optimizing network topology, it does not consider the coupling relationship between the GS and MS. The test case shows that the power system scale is small and only for the weekly time scale. To minimize the combined cost of power generation and maintenance, the security-constrained unit commitment (SCUC) problem must first be solved. With the diversification of power sources and the expansion of the power system scale, the SCUC problem has been the research focus for a long time [9]-[12]. The primary solutions include reducing the model size, identifying effective constraints, and introducing new intelligent algorithms.

The joint optimization of GS and MS is a common technical solution to the MS problem [13]-[17]. In [13], a reliability-based joint optimization model for GS and MS was proposed, in which the genetic algorithm and quadratic programming algorithm were used to solve the model. Although the literature reconstructed the reliability index under uncertainty factors, it did not consider the prediction error of renewable energy and load, while the power system scale of the test case is small, and the calculation efficiency of the model and algorithm was not mentioned. An approach to such an integrated GS and MS formulation that considers N−1 contingency constraints was proposed in [18], [19]; however, it ignored the impacts of the GC and the operation constraints of the units on maintenance determination. Furthermore, in the medium- and long-term time domains, forecasting uncertainty typically has an impact on decision-making in a power system [20]-[22]. In [20], both the MC and minimum expected power shortage based on risk assessment were considered. A multi-objective optimization model of MS was established, providing a reference technical guide for MS considering multiple objectives. A stochastic model coordinated with a long-term MS model of generation units and transmission lines with short-term SCUC was presented in [21], and the influence of uncertainty on maintenance scheduling was considered by involving random scenarios. Even though the MS optimization model and random influence were considered comprehensively, the calculation time was up to dozens of hours. In [22], based on the Monte Carlo simulation method, a short-term MS optimization model under the influence of random factors was constructed. The model considered the relatively complete generation and maintenance constraints. However, the monthly maintenance optimization on the IEEE 118-bus system required dozens of hours.

Based on the comprehensive analysis of the literature, the research on MS still suffers from the following primary challenges: ① it is difficult to obtain the global optimal solution due to the decoupling optimization of MS and GS; ② the impact of renewable energy and load uncertainty is not considered in the joint optimization model of MS and GS, and thus, the potential risk cannot be reasonably estimated; and ③ most models and algorithms are only applied to small-scale power systems, thus the involvement of uncertainty results in a general problem of insufficient computational efficiency. To address these issues, a security-constrained TTMS optimization model considering maintenance, generation, and operational risk costs (ORCs) is proposed in this paper. The refined model considers the impacts of equipment outages on renewable energy accommodation and market power purchase costs, which can effectively reduce the adverse effects of network topology changes. The primary contributions of this paper are summarized as follows.

1) A generation-maintenance joint optimization model with multiple objectives and comprehensive constraints is proposed. The simultaneous and mutual exclusion constraints of equipment are added based on the traditional TTMS constraints, and the flexible section limit constraints related to maintenance are added in the SCUC model.

2) To determine the possible operational risks of the maintenance results, a max-min double-layer optimization model that considers the stochastic effects of renewable generation, load forecasting, and $N-1$ faults is proposed and presented in this paper.

3) An iterative generation-maintenance algorithm is proposed to maintain a good balance between the accuracy and efficiency of the solution. Changes in the generation and ORCs are fed back to the maintenance optimization model in terms of the maintenance operation cost (MOC). This process ensures the overall optimization of maintenance and generation, even when the primary model for maintenance optimization does not consider the operation status of the power system.

4) The strength of the electrical coupling is proposed as an index and indicator of simultaneous shut-down and mutual exclusion, which can effectively avoid overlapping maintenance of the associated equipment. Thus, a few simultaneous maintenance operations of the associated equipment can significantly reduce the number of iterations of the algorithm proposed in this paper and thus further improve its efficiency.

The remainder of this paper is organized as follows. Section II introduces the newly established security-constrained transmission maintenance optimization model. Section III proposes an ORC model. Section IV proposes and describes an iterative generation-maintenance algorithm. Section V investigates the IEEE 118-bus system as a test case to simulate and verify the proposed model and algorithm. Finally, Section VI draws the primary conclusions.

II. Security-constrained Transmission Maintenance Optimization Model

A. Optimization Objectives

The optimization objective of the proposed model is to minimize the sum of the GC, MC, and ORC, i.e., load shedding compensation cost. The load shedding compensation cost refers to the fee that should be paid to any load when it must be cut off due to an $N-1$ fault under a specific maintenance scheme:

$$\begin{cases} \min F = f_1 + f_2 + f_3 \\ f_1 = \sum_{t=1}^{Tp}\sum_{i=1}^{N} S_{i,t}^{s} F(p_{i,t}) + \sum_{t=1}^{Tp-1}\sum_{i=1}^{N} S_{i,t+1}^{s}(1 - S_{i,t}^{s}) U(p_{i,t}) \\ f_2 = \sum_{k=1}^{K}\sum_{d=1}^{D} S_{k,d}^{m} c_{k,d} \\ f_3 = \varphi \sum_{t=1}^{Tp}\sum_{l_d=1}^{L_d} \delta_{ld,t} \Delta p_{ld,t} \end{cases} \tag{1}$$

In this paper, the time resolution is in hours, and there are 720 hours in one month. D is set to be 30 days in an entire month. For $S_{i,t}^{s}$, 1 implies start-up, and 0 implies shut-down. $U(p_{i,t})$ includes both the cold and hot start-up costs. The piecewise linear costs are used for $F(p_{i,t})$, which can typically be divided into five sections. For $S_{k,d}^{m}$, 1 implies there is maintenance, and 0 implies there is no maintenance. φ is a determined boundary parameter, which can be obtained by Monte Carlo simulation or based on practical experience or historical statistical data.

B. TTMS Constraints

The constraints relevant to TTMS include maintenance time, concurrent stop, mutual exclusion, and maintenance resource constraints.

1) Maintenance Time Constraints

$$\begin{cases}\sum_{t=d_0}^{d_1} S_{k,d}^m = J_k \\ d_1 - d_0 - 1 = J_k\end{cases} \tag{2}$$

Equation (2) implies that equipment maintenance must meet duration requirements and be in a continuous maintenance state.

2) Simultaneous Maintenance Constraints

A concurrent stop constraint implies that the equipment that can be maintained in one outage should be maintained simultaneously to avoid repeated outages:

$$\begin{cases}S_{k,d}^m \leq S_{k',d}^m \\ J_k \leq J_{k'}\end{cases} \tag{3}$$

Formula (3) implies that if equipment k and k' must be maintained simultaneously and the duration of equipment k is less than that of equipment k', then when equipment k is in a maintenance state, equipment k' must also be in a maintenance state. This result will ensure that this constraint is for the simultaneous maintenance.

3) Mutual Exclusion Constraints

A mutual exclusion constraint implies that, to ensure the transmission capacity of the power system and avoid the occurrence of isolated regions, some equipment should not be maintained simultaneously. A mutual exclusion constraint is expressed as:

$$S_{k,d}^m + S_{k',d}^m \leq 1 \tag{4}$$

Formula (4) implies that equipment k and equipment k' cannot be maintained simultaneously.

4) Maintenance Resource Constraints

$$\sum_{k=1}^{K} S_{k,d}^m \gamma_{k,d} \leq R_d \tag{5}$$

The resources in the definitions of $\gamma_{k,d}$ and R_d refer to the human and material resources required for the conducted equipment maintenance.

Based on the above model, the MC can be minimized by considering maintenance constraints. However, the generation and ORCs in the optimization model cannot be considered. To accurately consider the GC, the unit commitment problem must be included in the maintenance optimization model.

C. SCUC Constraints

SCUC constraints include load balance constraints, positive and negative reserve constraints, unit operation constraints, branch and transmission section limit constraints, etc., which have been presented in many references. A brief introduction is as follows.

1) Load Balance Constraints

$$\sum_{l_d=1}^{L_d} p_{l_d,t} - P_{T,t} = \sum_{i=1}^{N} p_{i,t} S_{i,t}^s \tag{6}$$

2) Positive and Negative Reserve Constraints

$$\begin{cases}\sum_{i=1}^{N} (p_{i,\max} - p_{i,t}) S_{i,t}^s \geq P_{u,t} \\ \sum_{i=1}^{N} (p_{i,t} - p_{i,\min}) S_{i,t}^s \geq P_{d,t}\end{cases} \tag{7}$$

The maximum output of the renewable energy unit equals its prediction, which can provide lower reserves but not upper reserves. In this paper, both positive and negative reserve demands are considered to be 15% of the total system load.

3) Unit Operation Constraints

The constraints include those of the unit output limit, unit ramp, and maximum number of unit start-up and shut-down times, which are expressed as:

$$\begin{cases}p_{i,\min} S_{i,t}^s \leq p_{i,t} \leq p_{i,\max} S_{i,t}^s \\ P_{i,t} - P_{i,t-1} \leq p_{i,up} \\ P_{i,t-1} - P_{i,t} \leq p_{i,down} \\ \sum_{t=1}^{Tp} S_{i,t+1}^s (1 - S_{i,t}^s) \leq S_{N,t}\end{cases} \tag{8}$$

The time constraints of the unit start-up and shut-down are expressed as:

$$\begin{cases}B_{i,t}^{off} - (S_{i,t} - S_{i,t-1}) B_{i,off} \geq 0 \\ B_{i,t}^{on} - (S_{i,t-1} - S_{i,t}) B_{i,on} \geq 0\end{cases} \tag{9}$$

4) Branch and Transmission Section Limit Constraints

A DC power flow method is used in this paper. The thermal stability limit constraints of the branches are expressed as:

$$\begin{cases}\boldsymbol{Z} = \boldsymbol{G}(S_{k,d}^m) \\ \boldsymbol{\theta} = \boldsymbol{Zp} \\ l_{b,t} = (\theta_{bh,t} - \theta_{bt,t})/x_b \\ l_{b,t} \leq l_{b,\max}\end{cases} \tag{10}$$

where $\boldsymbol{Z}$ depends on the state of the transmission equipment and connection relationship.

Transmission section limit constraints are expressed as:

$$\begin{cases}M_{E,t} \leq M_{E,t,\max} \\ M_{E,t} = \sum_{b \in E} l_{b,t}\end{cases} \tag{11}$$

As the security constraints in the GS model consider the impacts of the TTMS on the grid topology and the transmission limit, if the SCUC satisfies the security constraints, the corresponding TTMS also meets the security constraints.

D. Coupling of SCUC and TTMS Constraints

The TTMS leads to the transfer of power flow, which could reduce the transmission capacity of the power system. The additional increase in branch power may trigger branch thermal stability limit constraints. The decrease in available transmission capacity may trigger the transmission section limit constraint. Also, the unit commitment or output result will be adjusted, leading to a higher GC. However, TTMS will directly change the grid connection relationship, which will affect the calculation of $\boldsymbol{Z}$ in (10) and the value of

$M_{E,t,\max}$ in (11). In the traditional SCUC model, the TTMS is a boundary value; thus, the impedance matrix vector can be directly modified according to the maintenance results, and the transmission section limit can be determined correspondingly by matching. When maintenance becomes a decision variable, the impedance matrix vector and the section limit should be calculated dynamically according to the maintenance state variables, which is called the dynamic section limit.

For example, under the assumption that Section E is composed of L branches, the limit of Section E can be expressed as:

$$M_{E,d,\max}=\begin{cases} M_{E,1} & \sum_{lm\in E} S_{lm,d}^{m}=L \\ M_{E,2} & \sum_{lm\in E} S_{lm,d}^{m}=L-1 \\ M_{E,3} & \sum_{lm\in E} S_{lm,d}^{m}=L-2 \end{cases} \tag{12}$$

When the section members are not maintained, the limit is $M_{E,1}$, and when one or two members are maintained, the limit is changed to $M_{E,2}$ or $M_{E,3}$. In practice, the impacts of outages of different objects on these limits may be different, increasing the complexity of the quantification of the relationships between the section limits and equipment maintenance. However, the relationship can be expressed as logical expressions of the maintenance states.

If the impacts of the TTMS on the power flow as well as the transmission section limits are not considered, the accuracy of the optimization results will deteriorate significantly.

Although the MC and GC can be considered in the TTMS optimization model with SCUC, this still does not include the impact of the operational ORC in TTMS.

III. Proposed ORC Model

Renewable energy and load forecasting errors, equipment maintenance, and $N-1$ failures may lead to load shedding. The simultaneous occurrence of these events will significantly increase the probability of load shedding. This paper defines load shedding as system operational risk. When an operational risk occurs, load shedding becomes a necessary measure to ensure stable operation of the power system. In this paper, the load shedding compensation cost is the ORC. However, two problems must be solved to determine the load shedding compensation. First, when considering the renewable energy and load forecasting errors and $N-1$ failures, load shedding is a random scenario, and a concrete scenario must be specified to calculate the compensation cost. A common solution is to adopt a multi-scenario simulation method or the worst-scenario evaluation method. Second, load shedding is also an optimization problem, and it is necessary to construct an optimization model to reduce the total load shedding to the maximum extent by adjusting the unit commitment or output. To overcome the above problem, this paper uses a robust optimization method to determine the scenario with the maximum load reduction to evaluate the ORC. This process transforms the ORC calculation into a max-min double-layer optimization problem.

A. Max-min Double-layer Optimization Problem

1) Optimization Objectives

When there are fluctuations in the load, renewable energy generation, or random faults in a transmission line, the load connected to the node can be classified into three states: ① the load is unaffected by the fault; ② the load is completely separated from the power system; and ③ due to the limitation of the power system transmission capacity, a portion of the load must be cut off. The load that is completely separated from the power system can be obtained directly by a topology analysis. The partial cut-off load caused by the transmission capacity of the power system must be obtained using an optimization model. The optimization model of partial load compensation caused by equipment failure, load, and fluctuation in renewable energy generation is introduced next.

The scenario with the highest cost of load shedding compensation is defined as the extreme scenario, whose compensation cost is represented by f_3 in (1). The optimization model of partial load compensation is a max-min double-layer optimization problem expressed as:

$$\max\left\{\min\sum_{t=1}^{Tp}\sum_{l_d=1}^{L_d}\delta_{l_d,t}\Delta p_{l_d,t}\right\} \tag{13}$$

The optimization objective of the lower level lies in the minimum compensation value achieved by adjusting the unit output after an $N-1$ fault in a specific maintenance scenario. The upper maximum optimization involves finding the most severe $N-1$ fault in a specific maintenance scenario.

2) Constraints

Different relevant constraints include load balance constraints, positive and negative reserve constraints of the system, operating constraints of a unit, and branch/section limit constraints. The above constraints are similar to those expressed in (6)-(12), but the load and wind power shedding variables must be introduced into the equations (e.g., (6)), and the balance constraint must be adjusted to:

$$\sum_{l_d=1}^{L_d}(p_{l_d,t}-\Delta p_{l_d,t})-P_{T,t}=\sum_{i=1}^{N}p_{i,t}S_{i,t}^{s} \tag{14}$$

B. Calculation of $N-1$ Fault

The risk assessment model is a max-min double-layer optimization problem. To ensure the solving efficiency of the model, the solution of the $N-1$ fault must be explained in detail. To avoid an $N-1$ failure analysis for all devices, the following strategy is used in this paper.

1) The double-layer optimization model does not contain $N-1$ decision variables. $N-1$ is the boundary condition of the double-layer optimization model. If the number of $N-1$ scenarios to be resolved through the optimization is C_{n-1}, the double-layer optimization model must be conducted C_{n-1} times. To improve the computing efficiency, it is a key issue to reduce the number of $N-1$ scenarios.

2) If the $N-1$ fault causes a partial load to be completely disconnected from the power system, the equipment fault should be listed as an object of risk assessment. In this scenario, the max-min double-layer optimization problem does

not need to be resolved.

3) If the maintenance object is a member of the transmission section, an $N-1$ risk assessment should be conducted for the other members of the same transmission section.

4) An $N-1$ power flow transfer analysis is conducted under the base state condition. If the residual capacity of the branch or section is less than 10% after disconnection, equipment failure is listed as a risk assessment object.

For an $N-1$ fault, the new power flow distribution can be obtained directly by modifying the original power flow using a branch outage distribution factor without any disconnection in the power system:

$$\begin{cases} D_{a\text{-}b} = \dfrac{z_{a\text{-}b}/x_b}{1 - z_{b\text{-}b}/x_b} \\ \Delta p_a^b = D_{a\text{-}b} S_{f,b} p_b \end{cases} \tag{15}$$

Both $z_{a\text{-}b}$ and $z_{b\text{-}b}$ can be determined according to the node impedance matrix of the initial grid topology. For $S_{f,b}$, 1 implies a fault state.

C. Solution of Max-min Double-layer Optimization Problem

The methods to solve the max-min double-layer optimization problem primarily include the dual transformation method and the Karush-Kuhn-Tucker (KKT) condition method. The KKT condition is necessary to make a group of solutions become the optimal, which can transform the optimization problem into an equation for solving the problem; thus, the double-layer optimization problem can be transformed into a single-layer optimization problem. When the original problem is convex, the KKT condition is also a sufficient condition. The double-layer optimization problem proposed in this paper does not involve unit commitment. $N-1$ constraint is given to the model as a boundary condition through prejudgment. Therefore, the model is a linear optimization problem. The double-layer optimization problem can be converted into a single-layer optimization problem by the KKT condition.

Setting λ as the dual variable of the original subproblem, based on the complementary relaxation theorem, the subproblem of the original double-layer optimization problem can be expressed as:

$$\begin{cases} \text{SP: } S(\boldsymbol{y}) = \max\min \boldsymbol{dx} \\ \text{s.t. } \boldsymbol{Ex} \ge \boldsymbol{f} \end{cases} \tag{16}$$

It can be transformed into:

$$S(\boldsymbol{y}) = \max \boldsymbol{dx} \tag{17}$$

s.t.

$$\boldsymbol{Ex} \ge \boldsymbol{f} \tag{18}$$

$$\boldsymbol{E}^{\mathrm{T}} \boldsymbol{\lambda} \le \boldsymbol{d}^{\mathrm{T}} \tag{19}$$

$$(\boldsymbol{d}^{\mathrm{T}} - \boldsymbol{E}^{\mathrm{T}} \boldsymbol{\lambda})_i x_i = 0 \quad \forall i \tag{20}$$

$$(\boldsymbol{Ex} - \boldsymbol{f})_j \lambda_j = 0 \quad \forall j \tag{21}$$

$$\begin{cases} \boldsymbol{x} \ge \boldsymbol{0} \\ \boldsymbol{\lambda} \ge \boldsymbol{0} \end{cases} \tag{22}$$

$$\begin{cases} x_i \le M\delta_i \\ (\boldsymbol{d}^{\mathrm{T}} - \boldsymbol{E}^{\mathrm{T}} \boldsymbol{\lambda})_i \le M(1-\delta_i) \quad \forall i \\ \delta_i \in \{0, 1\} \end{cases} \tag{23}$$

$$\begin{cases} \lambda_j \le M\theta_j \\ (\boldsymbol{Ex} - \boldsymbol{f})_j \le M(1-\theta_j) \quad \forall j \\ \theta_j \in \{0, 1\} \end{cases} \tag{24}$$

Equation (16) is the original subproblem constraint, (18) and (19) are the dual-problem constraints, and (20) and (21) are the complementary relaxation conditions. Although the corresponding constraints of the complementary relaxation conditions are nonlinear, they are in different forms where two nonnegative variables are multiplied to zero, which can be linearized into the constraints in (23) and (24) using the large-M method.

Therefore, the original max-min double-layer optimization problem is transformed into a 0-1 mixed-integer programming problem, which can be solved directly.

IV. Proposed Iterative Generation-maintenance Algorithm

Due to multiple decision variables, multiple calculation periods, and complex constraint conditions of the joint optimization model of maintenance and generation, the decomposition-coordination algorithm is primarily used to solve it. Furthermore, the impact of equipment outages on power flow transfer and section limits needs to be taken into account, making it even more challenging to solve the model directly. The impacts of the TTMS on GS and potential security risk can be reflected in the economic cost. Assuming that all types of costs corresponding to different maintenance combination modes in each period can be fully and accurately quantified, the optimal maintenance combination results considering all types of costs can be obtained by solving the TTMS optimization model. Using the SCUC model and the ORC model, the impacts of maintenance on the GC and ORC can be fed back. Therefore, this paper proposes an iterative algorithm based on target cost feedback. The core of cost feedback is to measure the impact of maintenance on power GC and ORC. If there are multiple pieces of equipment that must be repaired, it is necessary to measure different maintenance combinations one by one. The entire process is similar to the enumeration algorithm. However, as the increase in maintenance equipment in the same period will not lead to a reduction in additional costs, the algorithm proposed in this paper is a directional enumeration algorithm that can accurately determine the termination conditions of enumeration. To improve the enumeration efficiency, the electrical correlation coupling coefficient is also introduced to participate in the model construction.

A. Overall Concept of Proposed Algorithm

The overall concept of the proposed algorithm is shown in Fig. 1. The joint optimization model can be divided into TTMS, SCUC, and operational risk models to be resolved. TTMS is mainly used to solve MS and provide the determined grid topology and transmission section limits based on the obtained maintenance results. The optimization objectives and constraints of the TTMS model remain unchanged in each iteration step, and it mainly updates the optimization results based on the cost feedback from the SCUC and ORC models. The determined maintenance results, power system topology, and transmission section limits are the boundary conditions for the SCUC and ORC models. SCUC is used to solve the additional cost of generation caused by maintenance. Meanwhile, the unit commitment results obtained by the SCUC model are treated as the boundary of the ORC model as well. Simultaneously, the max-min double-layer optimization problem is used to calculate the ORC. The SCUC and ORC models only provide the cost information to the TTMS model, without any constraint information. Therefore, there are three key problems that must be solved. ① Do the TTMS results influence the GC? ② How can the ORC be determined based on the TTMS results? ③ If the TTMS results affect the GC, how can the TTMS results be adjusted to compensate for the impacts on the GC and ORC?

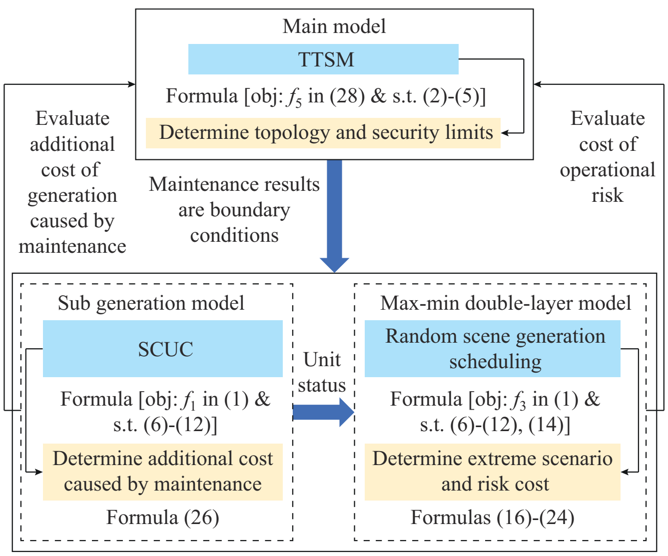

Fig. 1. Schematic of model structure.

B. Construction of MOC Model

For Problem ①, it is easy to obtain an answer. Due to equipment outages caused by maintenance, the original GC may increase or remain unchanged. Therefore, the effect of maintenance on the GC can be determined by comparing the GC before and after maintenance.

Definition 1: initial generation cost (IGC). The GC without considering any maintenance on day d is called the IGC, denoted as r_d.

Definition 2: generation cost under maintenance (GCM). The GC considering the equipment maintenance set $\Phi_d=\{S^m_{1,d}, S^m_{2,d}, \ldots, S^m_{K,d}\}$ on day d is called the GCM, denoted as $r_{\Phi,d}$. The GCM is defined as the maximum value when there is a network violation that cannot be eliminated due to outages during maintenance.

Definition 3: MOC. The increased GC considering the maintenance set Φ_d on day d is called the MOC, denoted as $r'_{\Phi,d}$. Expectedly, $r'_{\Phi,d}=r_{\Phi,d}-r_d$.

For Problem ②, under the given TTMS results, the max-min double-layer optimization can be used to solve Problem ②. The key step is finding a method for using the risk cost for TTMS optimization, which will be introduced and explained in the following description.

For Problem ③, the key step lies in developing a method for accurately establishing a logical relationship between $r'_{\Phi,d}$ and equipment maintenance; therefore, it can be reflected in the maintenance optimization model. This process allows us to simultaneously consider both maintenance and operation costs in the TTMS optimization model. The desired improvement in the TTMS optimization objective f_2 is transformed to f_4, and can be expressed as:

$$f_4=\sum_{k=1}^{K}\sum_{d=1}^{D}S^m_{k,d}c_{k,d}+\sum_{d=1}^{D}r'_{\Phi,d} \tag{25}$$

where $r'_{\Phi,d}$ depends on the impacts of the equipment maintenance set Φ_d on the GC. Simultaneously, the equipment maintenance set Φ_d affects the MC. In the maintenance model, $S^m_{k,d}$ denotes decision variables. Therefore, in the optimization model for maintenance, the association between $r'_{\Phi,d}$ and maintenance status $S^m_{k,d}$ is expressed as:

$$\begin{cases} r'_{\Phi,d}=\sum\limits_{n=1}^{K}\psi_{d-n} \\ \psi_{d-1}\geq\sum\limits_{k=1}^{K}S^m_{k,d}r'_{k-1,d} \\ \psi_{d-2}\geq\sum\limits_{i_1=1}^{K}\sum\limits_{i_2=1}^{K}(S^m_{i_1,d}+S^m_{i_2,d}-1)r'_{i_1-i_2,d} \quad i_1\neq i_2 \\ \vdots \\ \psi_{d-K}\geq\sum\limits_{i_1=1}^{K}\sum\limits_{i_2=1}^{K}\cdots\sum\limits_{i_K=1}^{K}\left(\sum\limits_{k=i_1}^{i_K}S^m_{k,d}-K+1\right)r'_{i_1-i_2-\ldots-K,d} \quad i_1\neq i_2\neq\ldots\neq i_K \end{cases} \tag{26}$$

We define a nonnegative number ψ_{d-n} to represent the MOC of the simultaneous maintenance of n equipment on day d. Therefore, the physical meaning of $r'_{i_1-i_2-\ldots-K,d}$ is clarified.

From (26), the following remarks can be inferred.

1) If only equipment k is under maintenance on day d, $S^m_{k,d}=1$, $\psi_{d-1}=r'_{k-1,d}$, and $\psi_{d-2}-\psi_{d-K}$ can only be set to be zero. If equipment i_1 and equipment i_2 are under maintenance on day d, $S^m_{i_1,d}=S^m_{i_2,d}=1$, $\psi_{d-1}=r'_{i_1-1,d}+r'_{i_2-1,d}$, $\psi_{d-2}=r'_{i_1-i_2,d}$, and $\psi_{d-3}-\psi_{d-K}$ can only be set to be 0.

2) If the operation cost of all maintenance combinations must be determined, the calculation burden is high. However, in practice, the K pieces of equipment to be repaired are more evenly distributed, and equipment outage does not typically increase the GC. Therefore, the MOC includes many zero values, leading to a significant reduction in the calculation scale.

Based on the calculation of the MOC, the calculated ORC can be included in the calculation of $r'_{\Phi,d}$. Therefore, the ORC corresponds to the combination of the maintenance equipment. The risk and MOC are fed back to the main model of TTMS optimization to guide the maintenance optimization adjustment.

C. Avoiding Simultaneous Maintenance of Strongly Associated Equipment

The construction of (26) is a key factor affecting the solving performance of the model. To reduce the number of computations, a feasible measure is to reduce the increase in the cost caused by an overlapping of the maintenance of different equipment. The equipment outage causes power flow transfer, and the load rate of the equipment to take a portion of the transfer power flow increases. In the case of power flow overlapping transfer due to multi-equipment outages, the probability of the network overlimit may increase, and consequently, the operation cost may increase. By virtue of the electrical correlation coupling coefficient index, the probability of power flow overlapping transfer decreases:

$$\begin{cases} D_{a\text{-}b}=\dfrac{z_{a\text{-}b}/x_b}{1-z_{b\text{-}b}/x_b} \\ D_{ab}=\dfrac{1}{1-D_{a\text{-}b}D_{b\text{-}a}} \end{cases} \tag{27}$$

If $D_{a\text{-}b}$ and $D_{b\text{-}a}$ are small, the two pieces of equipment are weakly associated, and D_{ab} approaches 1. In this paper, according to the example test, if $D_{ab}>1.2$, the relevant equipment can be inferred to be strongly associated. When any two pieces of equipment are strongly associated, a penalty is added to f_4. The improvement in the maintenance optimization objective f_4 is adjusted to f_5 and can be expressed as:

$$f_5=\sum_{k=1}^{K}\sum_{d=1}^{D}S_{k,d}^{m}c_{k,d}+\sum_{d=1}^{D}r'_{\Phi,d}+\sum_{d=1}^{D}\sum_{v_1=1}^{K}\sum_{v_2=1}^{K}(S_{v_1,d}^{m}+S_{v_2,d}^{m}-1)p_{v_1\text{-}v_2} \tag{28}$$

In this paper, the correlation coefficient of two pieces of equipment is to be zero if D_{ab} is less than 1.2.

D. Pseudocode of Proposed Algorithm

Based on the previous description, the pseudocode of the proposed algorithm is shown in Algorithm 1.

Algorithm 1: pseudocode of proposed algorithm

Begin
Input boundary data
Calculate D_{ab}
If $D_{ab}>1.2$ **then**
  Add the penalty cost of simultaneous maintenance of equipment a and equipment b into the optimization objective
  Set $V=0$; simultaneous maintenance of V equipment
  Calculate *SCUC* and MOC^V
  Calculate double-layer optimization model and ORC^V
Do
  Set $V=V+1$
  Calculate SCUC and MOC^V
  Calculate double-layer optimization model and ORC^V
  Calculate daily distribution of MOC^V and ORC^V
  Calculate TTSM with daily distribution of MOC^V and ORC^V
While $|MOC^V-MOC^{V-1}|<\varepsilon_1$ and $|f_5^V-f_5^{V-1}|<\varepsilon_2$ (ε_1 and ε_2 are the given convergence criteria)
Break
Output result of TTSM and SCUC
End

E. Analysis of Convergence

The convergence of the proposed algorithm covers two main aspects: ① the convergence of the algorithm used to solve TTMS, SCUC, and ORC models; and ② the convergence of iterative calculations amongst SCUC, ORC, and TTMS models.

The convergence of TTMS and SCUC solving algorithms mainly depends on whether there are conflicts amongst constraints. ORC transforms a double-layer optimization problem into a single-layer optimization one for solution, essentially a security-constrained economic dispatch considering load shedding. The convergence of the above models can be effectively improved by identifying the constraint conflicts.

Meanwhile, the proposed iterative algorithm has a good convergence: firstly, the proposed algorithm does not add any new constraint to the main model, and so the iterative process does not deteriorate the convergence of the TTMS model, which is an advantage of the proposed algorithm; secondly, the algorithm proposed herein is essentially an enumeration algorithm, which can ensure the convergence of iterations without considering the time costs. Therefore, an improvement on the iteration efficiency is the core point of the algorithm, and the main ideas include: ① based on the physical characteristics of model, providing the specific enumeration direction to accelerate the convergence; and ② introducing electrical correlation coupling coefficients and setting iteration gaps to further improve the convergence efficiency of the algorithm.

V. Test Case and Analysis

In this paper, the interconnection system of the IEEE 118-bus system [23] with three areas (western, northern, and southern areas) is considered as a test case. For verification, it is necessary to make some changes to the power system and initial conditions, and the modifications are described as follows.

1) Three wind farms (units 55-57) are added at nodes 49, 80, and 118, and their predicted values are shown in Appendix A Fig. A1. This figure shows periods of high and low wind power generation across the month.

2) A monthly 720-point system load forecasting value is built, and the full month curve is shown in Appendix A Fig. A2.

3) Seventeen pieces of equipment maintenance (including four switches, which verify the simultaneous maintenance constraints) are undergoing, and the corresponding information is summarized in Appendix A Table AI. The daily maintenance resources are shown in Appendix A Fig. A3.

4) We assume that the daily MC of each piece of equipment is \$50 on normal working days, \$100 on weekends, and \$150 on legal holidays. The first day is a Monday, and the first three days are legal holidays.

5) The power limits of branches 153 and 159 are set to be 250 MW, and the power limits of the remaining branches are set to be 500 MW. To consider the impact of equipment maintenance on the section limit, it is assumed that the transmission section limit between the southern and northern areas of the power system is 1100 MW in the absence of equipment maintenance. The limit is reduced by 200 MW when one piece of equipment is out of service.

6) The fluctuation ranges of the wind power output and

the load power are assumed to be 15% and 5% of their predicted values, respectively. The most extreme scenario in risk assessment is avoidable, which makes the model rather conservative to directly send back the ORC of the most extreme scenario to the primary model; therefore, it is necessary to define the probability of extreme scenario, which is 1%. The compensation for load shedding is 100 $/MWh. Accordingly, the optimization software CPLEX is used to solve the optimization model in this paper. The hardware condition of the test case study in this paper is a portable computer with a CPU i5-5200 of 2.2 GHz with 16 GB memory.

Four modes are analyzed in this paper: in Mode 1, TTMS is performed without considering the GC and the ORC; in Mode 2, TTMS is performed by considering the GC; in Mode 3, TTMS considers the GC and ORC, and ORC is calculated through the double-level optimization algorithm proposed in this paper; and in Mode 4, TTMS is performed by considering the GC and ORC, in which the ORC is calculated by the Monte Carlo simulation method.

A. Maintenance Optimization Results Considering MOC

1) Analysis of MOC

With regard to the proposed algorithm, the key step is to calculate the additional GC caused by maintenance.

The single-equipment maintenance of branches 31, 33, 129, 160, and 174 at any time of the month does not affect the GC of the power system. When branches 98, 99, 118, 153, 159, 185, and 186 are maintained on a specific day of the month, the negative impact on the operation cost is reduced. Figure 2 shows the influence of branch 153 on the increase in MOC during maintenance on different days. Low-cost generation resources are limited due to insufficient transmission capacity, which is the key cause of the increase in GC and can be divided into the following two scenarios.

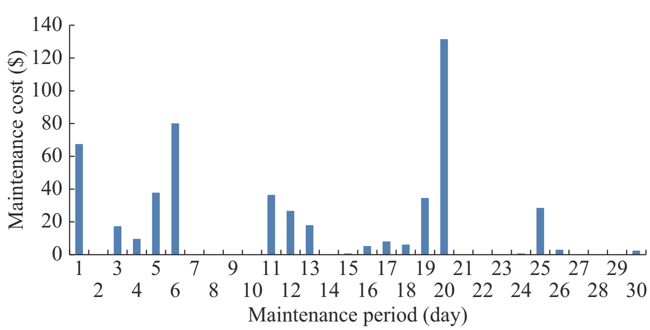

Fig. 2. Influence of branch 153 on increase in MOC during maintenance on different days.

1) Maintenance reduces the transmission limit. Branches 153 and 159 constitute the delivery section of unit 44. The maintenance of branches 153 and 159 leads to a unit output limitation. Due to differences in the load demand and the wind power output over the entire month, the MC is irregularly distributed during this time, as shown in Fig. 3. The power plant output limitation on the first day is also shown in Fig. 3. Branches 98 and 99 are members of the transmission section between the southern and northern areas, and their maintenance reduces the transmission section limit. The unit output must be adjusted to control the transmission section power. Figure 4 shows the section power adjustment caused by maintenance of branches 98 and 99 on the 28th day.

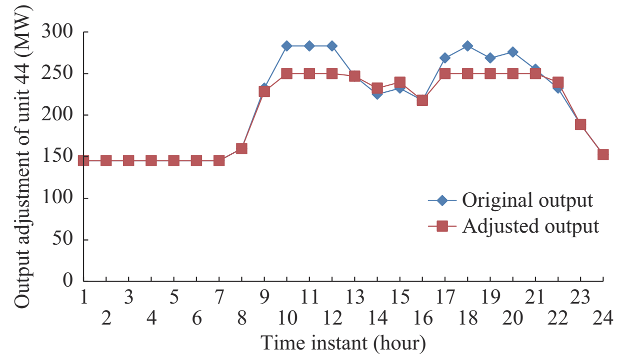

Fig. 3. Output adjustment of unit 44 caused by maintenance of branches 153 and 159 on the first day.

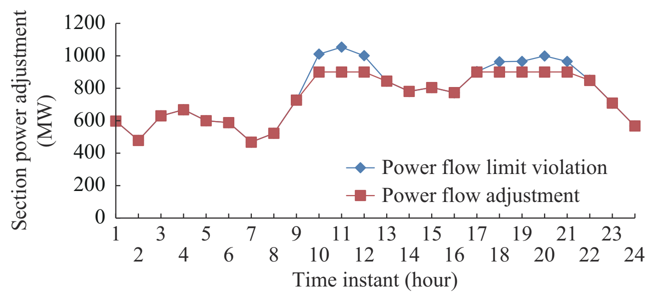

Fig. 4. Section power adjustment caused by maintenance of branches 98 and 99 on the 28th day.

2) After maintenance, the power flow transfer causes the power to exceed the constraint limit. The maintenance of either branch 185 or 186 transfers power flow to another line. Figure 5 shows the power flow adjustment of branch 185 caused by the maintenance of branch 186 on the 30th day. As branches 185 and 186 carry the task of wind power transmission, if the maintenance of branch 185 or 186 is arranged on the 30th day, the wind power is correspondingly reduced.

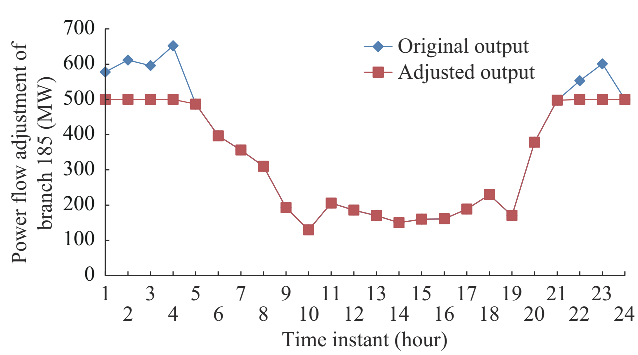

Fig. 5. Power flow adjustment of branch 185 caused by maintenance of branch 186 on the 30th day.

2) Impacts of MOC on Maintenance Optimization Results

The simulation results with and without considering the MOC are shown in Table I.

TABLE I
COMPARISON OF MOC AND MC IN MODES 1 AND 2

Mode	MC ($)	MOC ($)	Total cost ($)
Mode 1	5650	4685.50	10335.50
Mode 2	5650	66.75	5716.75

In Fig. 6, the red grid represents that the equipment has a maintenance status on that day. As shown in Fig. 6, the two modes can satisfy various maintenance constraints such as simultaneous shut-down, mutual exclusion, and maintenance resources. When the operation cost is considered, the maintenance periods of some equipment are adjusted to satisfy the needs of wind power integration (e. g., the maintenance of branch 118 is conducted ahead of time).

In terms of costs, in Mode 1, the MC is $5650, the MOC is increased by $4685.5, and the total cost reaches $10335.5. In contrast, Mode 2 can markedly reduce the MOC to $66.75. The MOC distribution on different days over one month is shown in Fig. 7. Thus, considering the MOC in the maintenance optimization model can lead to good economic benefits.

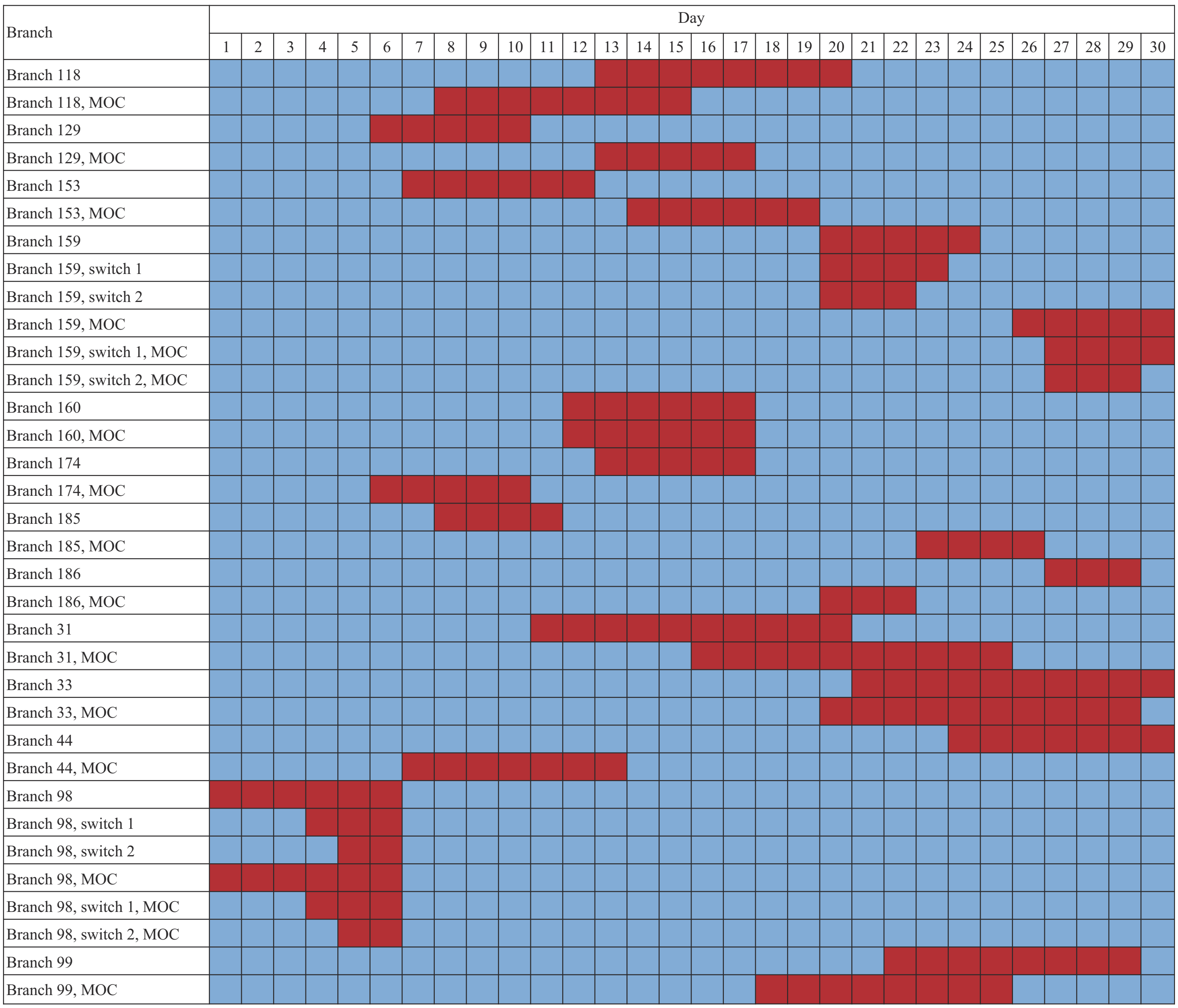

Fig. 6. Distribution diagram of maintenance results with and without considering MOC.

B. *Maintenance Optimization Results Considering MOC and ORC*

1) *Analysis of ORC*

Based on the uncertainty of wind power forecasting, load forecasting, and $N-1$ faults, this part presents an operational risk analysis conducted on the uncertainty of the maintenance results. The maintenance of branches 98 and 99 may lead to a load loss risk of insufficient power supply capacity in the northern area. By solving the operational risk model described in Section III, the maintenance of branches 185/186, 118, and 160 may lead to the loss of load risk of nodes 118, 76, and 101, respectively.

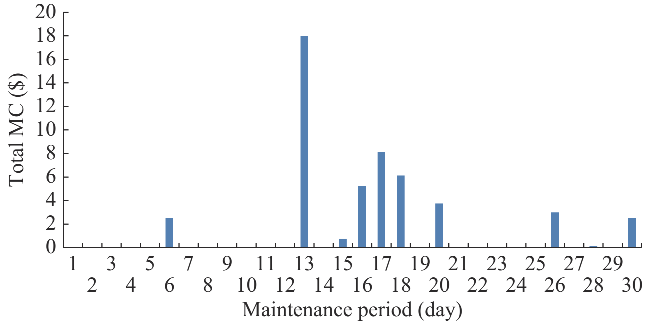

Fig. 7. Distribution of total MCs.

The daily distribution of the ORCs generated by the load shedding, which is caused by the maintenance of each line, is shown in Fig. 8.

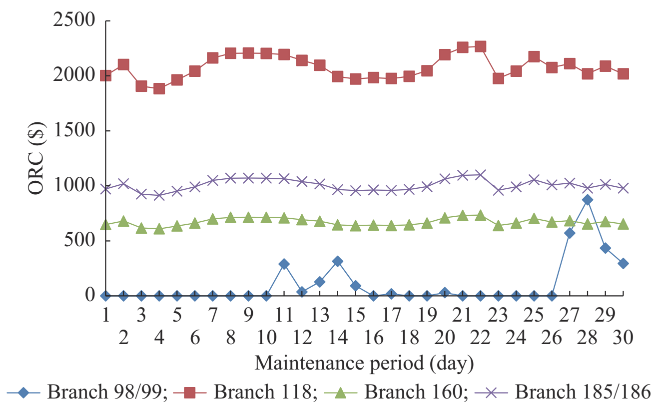

Fig. 8. Daily distribution of ORCs.

2) Influence of ORC on Maintenance Optimization Results

The simulation results with and without considering the ORC are shown in Table II and Fig. 9.

TABLE II
COMPARISON OF MOC AND MC UNDER MODES 2 AND 3

Mode	MC ($)	MOC ($)	ORC ($)	Total cost ($)
Mode 2	5650	66.75	28257	33973.75
Mode 3	5750	75.25	27246	33071.25

Figure 9 shows that the maintenance of some equipment is adjusted due to the consideration of the ORC (e.g., maintenance of branch 118 is postponed to the 16^{th}-19^{th} days when the ORC is lowered). Concurrently, considering the maintenance resource limitation of the 16^{th} day, the maintenance of branch 129, which is not related to the operational risk, is postponed to the 19^{th} day.

In terms of costs, in Mode 2, the ORC is $28257, and the total cost reaches $33973.75. In contrast, Mode 3 can reduce the ORC to $27246 and can reduce the ORC by $1011. However, the adjustment cost is only $108.50. Remarkably, the ORC changes the result of the maintenance plan and reduces the ORC under the maintenance boundary by a small increase in MC.

3) Comparative Analysis of Double-layer Optimization Problem and Scene Method

Risk assessment scenarios can be generated by Monte Carlo simulations. The ORC calculation based on Monte Carlo simulation is defined as Mode 4. The load and wind power forecasting errors follow a Gaussian distribution, in which the standard deviation of the load forecasting error is 1.5% and the wind power forecasting error is set to be 5%. The random failure of transmission equipment follows a uniform distribution, and the probability of failure is 1%. The example does not consider the simultaneous failure of two pieces of equipment. The generation-maintenance iterative algorithm proposed in this paper must calculate the daily risk cost of equipment maintenance throughout the month. Therefore, if the equipment fails in a certain scenario, it means that it will remain in the failure state for 30 days in this entire month. Only the equipment that may incur ORC shall be included in the equipment failure set. There are 100 scenarios used for risk assessment. For each of the 100 cases, the ORC is calculated based on the determined unit commitment results, and the average value of these 100 scenarios is considered to be the final ORC, as shown in Fig. 10.

Figure 10 differs from Fig. 8 in the following aspects. As there is no branch failure in 100 scenarios that causes branch 185/186 to result in ORC, there will be no ORC throughout the month after the maintenance of branch 185/186.

Conversely, according to the power system structure, there are 7 branches that may cause ORC after branch 98/99 maintenance, and five of 100 scenarios suffer from related branch failures; thus, the ORC of this maintenance is much higher in Mode 4 than in Mode 3. The above ORC is fed back to the maintenance optimization model, and the cost optimization results are shown in Table III.

Table III shows that there is a marginal difference between the MC and MOC values in Modes 3 and 4, while the decrease in the ORC value in Mode 4 is primarily attributed to the fact that the ORC of branch 185/186 is not included. Similarly, the maintenance scheduling results of all branches in the two modes are compared and analyzed, and only part of the maintenance periods of branches 33, 118, or 186 in Mode 3 are adjusted in Mode 4. The results show that the solution to the max-min double-layer optimization problem proposed in this paper and the Monte Carlo simulation method can achieve highly similar maintenance plans, and the analysis of computational burden will be discussed in the following subsection.

C. Computational Burden of Algorithm

1) Calculation Time Analysis of Proposed Generation-maintenance Iterative Algorithm and Comparison with Others

The proposed algorithm (i.e., Mode 3) can be divided into the generation, maintenance, and $N-1$ fault risk compensation models. The average time for each calculation during each iteration is listed in Table IV. TSC is the time consumption of a single calculation, and NTC is the number of times a calculation is performed.

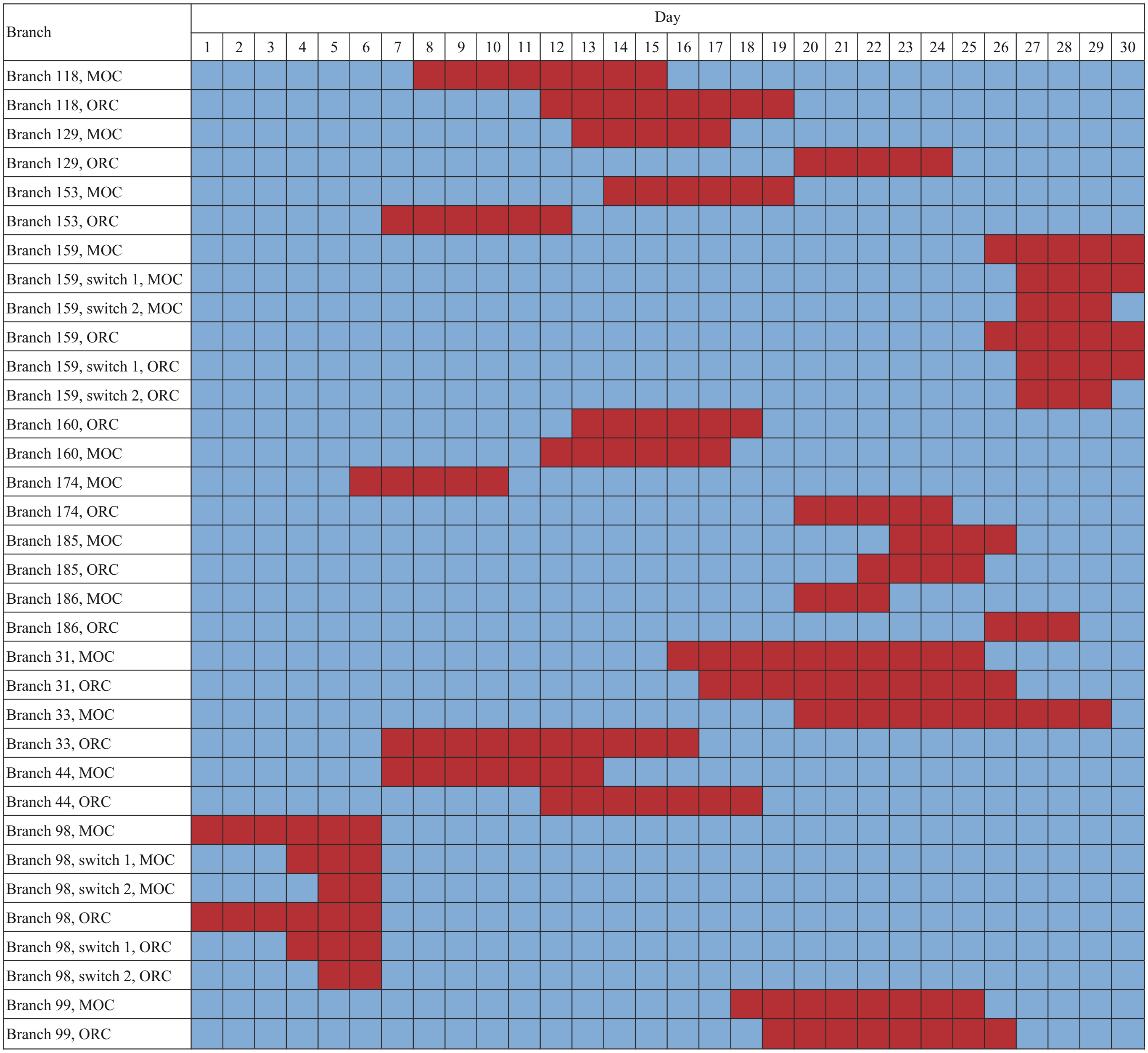

Fig. 9. Distribution diagram of maintenance results considering ORC.

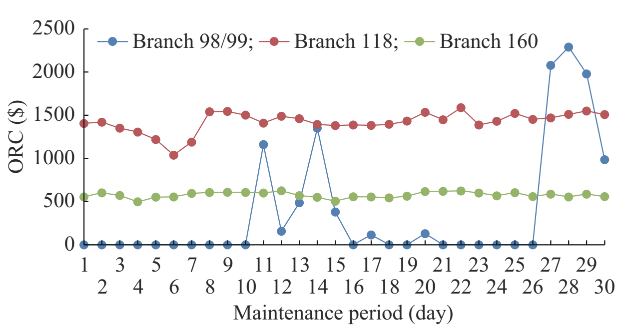

Fig. 10. Daily distribution of ORCs in Mode 4.

In this paper, in the execution process of the test case, the GS optimization model without considering any maintenance is calculated once. Correspondingly, an $N-1$ analysis is performed on the power generation results to determine whether the maintenance of equipment will increase the operation cost.

TABLE III
COMPARISON OF MOC AND MC IN MODES 3 AND 4

Mode	MC ($)	MOC ($)	ORC ($)	Total cost ($)
Mode 3	5750	75.25	27246	33071.25
Mode 4	5700	66.75	14341	20107.75

TABLE IV
COMPUTATIONAL BURDEN ANALYSIS OF PROPOSED ALGORITHM

Model	TSC (s)	NTC	Total time (s)
Generation model	305	6	1830
Maintenance model	14	3	42
ORC model (Mode 3)	634	2	1268
ORC model (Mode 4)	42	100	4200

Based on the analysis, for seven devices, their MOCs must be calculated using the GS optimization model. Combined with the topological connection characteristics of the equipment, the GS optimization model must be calculated four times. Based on the $N-1$ topology analysis and the power flow transfer analysis with maintenance as the boundary, the $N-1$ fault risk compensation model must be calculated twice. After TTMS, the GS optimization model is calculated once. Therefore, the GS optimization model must be conducted six times. When risk assessment is not considered, the total calculation time is approximately 30 min. If the risk analysis is complete, the calculation time increases to 51 min. The fast convergence of iteration is due to the introduction of the electrical correlation coupling coefficient into the model. In the previous subsection, the Monte Carlo method is used for operational risk analysis (Mode 4), which takes 42 s for each scenario and hence 4200 s for 100 scenarios; thus, its calculation time is as high as 3.3 times that of the double-layer optimization method (Mode 3).

The total time cost of the model and algorithm proposed in this paper is compared with [21], [22], and results are shown in Table V. Although there are some differences in the focus of these papers, the comparative analysis in Table V shows that the transmission maintenance optimization model and generation-maintenance iterative algorithm proposed in this paper have better efficiencies than existing methods. The ORC model in this paper is performed under the calculated unit commitment and maintenance results.

TABLE V
COMPUTATIONAL EFFICIENCY COMPARISON WITH DIFFERENT METHODS

Mode/case	Number of maintenance equipment	Number of time periods	Whether to consider uncertainty	Time cost (min)
Mode 3	17	720	Yes	52
Reference [21]	4	672	Yes	>240
Reference [22], case 4	4	672	Yes	>5000

2) Analysis of Influence of Coupling Coefficient on Proposed Generation-maintenance Iterative Algorithm

In the previous text, the statistics of the calculation time are obtained on the premise of considering the electrical correlation coupling coefficient proposed in this paper. In the case of simultaneous associated maintenance of multiple equipment, the calculation scale will increase markedly if the electrical correlation coupling coefficient is not considered, as in all the existing methods. The specific description is shown as follows.

The calculated electrical correlation coupling coefficients between two pieces of equipment under maintenance are listed in Table VI.

In Fig. 11, Y and N represent the TTMS optimization results of branches 31 and 33 with and without considering the electrical correlation coupling coefficient, respectively. Considering the electrical correlation coupling coefficient, branches 31 and 33 automatically avoid simultaneous maintenance due to the existence of a penalty cost. However, if the electrical correlation coupling coefficient is not considered, simultaneous maintenance occurs on the 21st-23rd days. The curves reaching the value of 1 represent the maintenance results considering the electrical correlation coupling coefficient, while the curves reaching the value of 2 represent those without considering it.

TABLE VI
ELECTRICAL CORRELATION COUPLING COEFFICIENTS

Equipment pair	Coupling coefficient
Branches 31-33	1.30
Branches 98-99	1.34
Branches 118-185	4.23
Branches 118-186	4.54
Branches 185-186	3.17
Branches 153-159	5.52

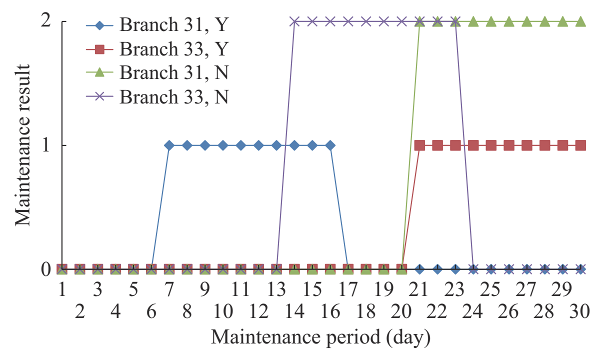

Fig. 11. Comparison of maintenance results with and without considering electrical correlation coupling coefficient.

If the results of the simultaneous maintenance of branches 31 and 33 are introduced into the SCUC model, the MOC is increased by \$978. Based on this investigation, the simultaneous maintenance of branches 31 and 33 results in a marked increase in the power flow of branch 38, which exceeds the transmission limit. The unit output must be adjusted to enable branch 38 to satisfy the requirements of the transmission limit. The adjustment of the unit output increases the cost of power generation by \$978. Based on the algorithm logic used in this paper, it is necessary to calculate the added value of the GC caused by the simultaneous maintenance of branches 31 and 33 during different periods.

At this time, an iterative calculation is required. For each iteration, it is necessary to calculate the GS optimization model 4 times, the TTMS optimization model once, and the ORC model twice, which is equivalent to doubling the calculation time, as shown in Table IV, thus resulting in a marked increase in the calculation time. However, iterative calculation can be effectively avoided by considering the electrical correlation coupling coefficient. Simulation results indicate that two iterations are required to achieve convergence without considering the electrical correlation coupling coefficient; otherwise, no iteration is conducted. Therefore, the computational efficiency of the proposed generation-maintenance iterative algorithm, benefitting from the novel electrical correlation coupling coefficient, is markedly improved.

VI. Conclusion

To comprehensively consider the impacts of transmission equipment maintenance on the entire system operation, a security-constrained transmission maintenance optimization model considering maintenance, generation, ORC, and grid security constraints is built. To achieve a high solution efficiency with the proposed model, a generation-maintenance iterative algorithm based on cost feedback and an electrical correlation coupling coefficient is proposed. Based on the analysis and verification, the following critical conclusions are drawn.

1) A reasonable arrangement of MS can effectively reduce the GC of a system and improve the renewable energy accommodation capacity, resulting in more benefits.

2) The optimization model is divided into maintenance, generation, and $N-1$ fault risk compensation models to calculate solutions iteratively. The proposed model can accurately consider the impacts of maintenance on the power flow and the section limit and thus reduce the complexity of the model solution.

3) Changes in the generation and ORC are fed back to the maintenance optimization model in the form of the MOC. This process ensures the overall optimization of maintenance and generation under the condition that the maintenance optimization model does not directly include the operation status of the power system.

4) Considering the electrical coupling degree of the equipment in this maintenance optimization model, it is possible to avoid overlapping maintenance of associated equipment and thus improve the solution efficiency of the joint optimization model.

To improve model accuracy and algorithm efficiency, this paper should be extended in two ways: ① the introduction of big data mining technology can determine the window period of equipment maintenance in advance, thus reducing the solution space of the optimization model and improving the solution efficiency with full consideration of operational risk; and ② by conducting grid equipment association analysis, the identification of a more appropriate combination of concurrent stop and mutual exclusion for the equipment to be repaired is required in advance to improve model efficiency.

Appendix A

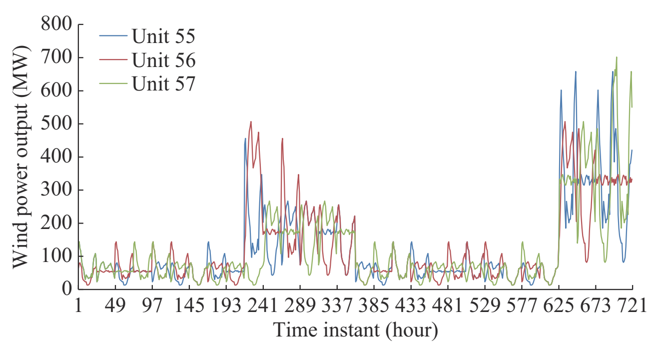

Fig. A1. Monthly wind power forecasting in each hour.

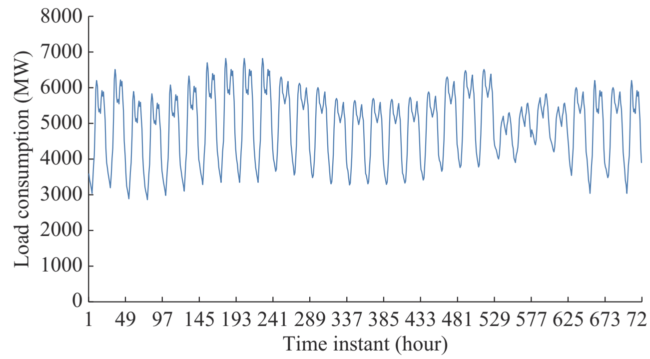

Fig. A2. Monthly load forecasting in each hour.

TABLE AI
Information on Transmission Lines to Be Repaired

Branch No.	Head and end nodes/switch	Scheduled duration (day)	Human and material resources (R_d in (5))
Branch 44	15-33	7	12
Branch 31	23-25	10	15
Branch 33	25-27	10	15
Branch 98	49-66	8	15
Branch 99	49-66	8	15
Branch 118	76-77	8	8
Branch 129	82-83	5	8
Branch 153	80-99	6	10
Branch 159	99-100	5	10
Branch 160	100-101	6	10
Branch 174	103-110	5	8
Branch 185	75-118	4	10
Branch 186	76-118	3	10
Branch 98	Switch 1	3	4
Branch 98	Switch 2	2	4
Branch 159	Switch 1	4	4
Branch 159	Switch 2	3	4

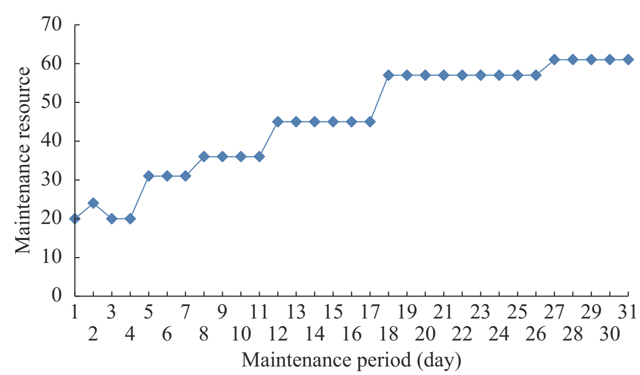

Fig. A3. Maintenance resources on different days in one month.

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Dan Xu received the B.S. and M.S. degrees in electrical engineering from China Agricultural University, Beijing, China, in 2007 and 2009, respectively. He received the Ph.D. degree in electrical engineering from China Electric Power Research Institute, Beijing, China, in 2022. He is a Senior Engineer in China Electric Power Research Institute. His interests include optimization operation of large-scale power systems and renewable energy integration.

Zhi Cai received the B.S. and M.S. degrees in electrical engineering from Tsinghua University, Beijing, China, in 2006 and 2009. He is a Senior Engineer in China Electric Power Research Institute, Beijing, China. His research interests include power system operation and planning, and renewable energy integration.

Qian Cheng received the M.Sc. degree in School of Electrical Engineering from Chongqing University, Chongqing, China, in 2023. Her research interests include hybrid AC/DC grid power flow algorithms, uncertainty quantifi cation analysis, and power system security risk assessment.

Guodong Huang received the B.Sc. degree in electrical engineering and automation from China Agricultural University, Beijing, China, in 2009, and the M.Sc. degree in power system and automation from China Agricultural University, in 2011. He is currently working as a Senior Engineer in China Electric Power Research Institute, Beijing, China. His research interests include grid dispatching automation, power system economic dispatching, and electricity markets.

Jingyang Zhou received the B.S. and M.S. degrees in electrical engineering from China Agricultural University, Beijing, China, in 1985 and 1988, respectively. She used to be a Senior Researcher at the China Electric Power Research Institute, Beijing, China, and is now retired. Her research interests include power system economic dispatching and electricity markets.

Junjie Tang received the Ph.D. degree in electrical engineering at the Institute for Automation of Complex Power Systems, E. ON Energy Research Center, RWTH Aachen University, Aachen, Germany, in 2014. He is currently an Associate Professor with the Power and Energy Reliability Research Center, State Key Laboratory of Power Transmission Equipment & System Security and New Technology, Chongqing University, Chongqing, China. His research interests include complex power system uncertainty quantification analysis, modeling of hybrid AC/DC grid, and application of machine learning in power systems.