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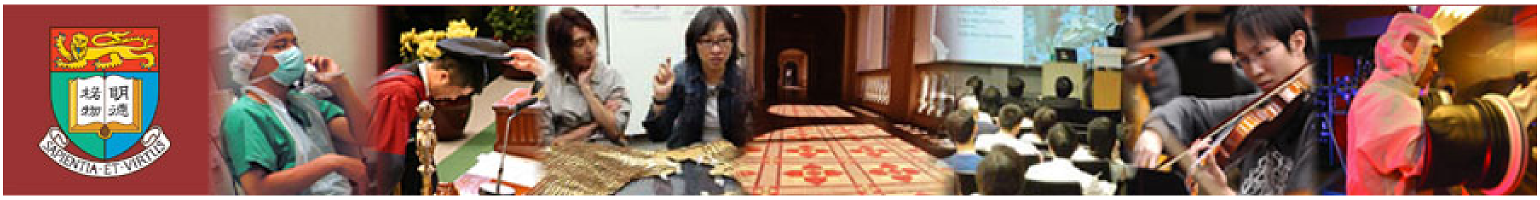

Title	Dynamic maintenance strategies for multiple transformers with Markov models
Author(s)	Wang, C; Zhou, H; Hou, Y; Liu, H
Citation	The 5th IEEE PES Innovative Smart Grid Technologies Conference (ISGT 2014), Washington, DC., 19-22 February 2014. In Innovative Smart Grid Technologies (ISGT) Proceedings, 2014, p. 1-5
Issued Date	2013
URL	http://hdl.handle.net/10722/204104
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Dynamic Maintenance Strategies for Multiple Transformers with Markov Models

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***Abstract*— Intelligent substations in smart grids can provide more information about operating states of transformers by advanced sensors and monitoring units. According to information, operators can identify health conditions of transformers more accurately to determine maintenance strategies more reasonably. Maintenance of transformers can enhance the health condition and improve the reliability of a power system. However, maintenance introduces additional costs into total operating costs. A sophisticated maintenance strategy should be a tradeoff between maintenance costs and reliability enhancement. Based on monitoring information, a dynamic coordinated maintenance strategy for multiple transformers is proposed in this paper. First, a Markov model of an individual transformer is built to demonstrate its deterioration processes. Based on deterioration processes of an individual transformer, deterioration processes of a system with multiple transformers are built. Besides internal deterioration processes of components, external conditions, e.g., weather conditions and availability of servicemen and auxiliary equipment, are also considered in the model. Then, an optimization model is built. A series of dynamic coordinated maintenance strategies can be provided by the proposed optimization model, which is solved by a backward induction algorithm. A test system is used to demonstrate efficiency and accuracy of the method proposed in this paper.**

***Index Terms*--Backward induction, dynamic coordinated maintenance strategies, Markov decision processes.**

I. INTRODUCTION

With the development of intelligent substations in smart grids, more information about operating states of transformers can be provided by advanced sensors and monitoring units equipped in intelligent substations. With provided information, operators can identify health conditions of transformers more accurately to determine maintenance strategies more reasonably. For a power system, electric power utilities always try to maximize profits with acceptable reliability levels. Challenges posed by aging equipment should be solved in a scheduled manner to minimize potential crises in the future. During the operating period of a transformer, the deterioration may increase the costs and decrease the reliability of the whole system. Usually, maintenance is used to mitigate the deterioration of components and enhance reliability levels of a system. However, additional costs associated with maintenance may increase the whole operating costs. To balance the reliability and costs, a sophisticated maintenance schedule is critical needed. The traditional maintenance is often pre-defined, i.e., maintenance activities are implemented in regular intervals. This method can be implemented with limited information of equipment but might be inefficient and uneconomic.

The importance of maintenance scheduling for aging components is well recognized [1]-[6]. A state diagram, represented by a Markov process, was employed to demonstrate the deterioration and maintenance [7], [8]. This state diagram can illustrate transition probabilities between different deterioration states. Based on state diagrams, paper [9] analyzed strategies for the enhancement of Markov models. Paper [10], [11] analyzed the optimal maintenance with the consideration of the power system operation. The genetic algorithm (GA) is used to optimize the model. However, in real systems, some external factors, like weather and auxiliary equipment, may influence the maintenance strategies. Therefore, based on more information about operating states of transformers in intelligent substations, deterioration processes of an individual transformer and multiple transformers, using Markov models, are built in this paper. Besides internal deterioration processes of components, external conditions, e.g., weather conditions and availability of servicemen and auxiliary equipment, are also considered in the model. Then, to represent current and successive influences, an expected cost-to-go is presented. A backward induction algorithm is employed to solve this model. A test system is shown to validate the proposed model and the method. The proposed model can provide operators a series of dynamic coordinated maintenance strategies to adjust different conditions of multiple transformers.

The paper is organized as follows: Section II describes deterioration models of an individual transformer and multiple transformers. Section III presents the proposed dynamic optimization model and a backward induction algorithm. A test system is shown in Section IV.

This work is partly supported by National Key Research Program of China (973 Program, 2012CB215102), National Natural Science Foundation of China (51277155) and Research Grant Council, Hong Kong SAR (GRF712411E and ECS739713).

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II. Markov Models for an Individual Transformer and Multiple Transformers

A. Deterioration Processes of an Individual Transformer Based on a Markov Model

For a transformer, its deterioration can be divided into several different levels which can be identified through information provided by sensors and monitoring units equipped in the intelligent substation. Assume that there are N types of deterioration levels, i.e., N states, for a transformer. The state set can be denoted as $\Theta_D = \{D_1, \cdots, D_N\}$. The first state is a best state and the Nth state is a failure state.

If there are not any activities, e.g. maintenance activities and repair activities, a worse state will not return to a better state. With increasing time intervals, a transformer will be in the failure state, i.e., D_N. The transitions between different states without any activities, i.e., maintenance activities and repair activities, are shown in Fig.1.

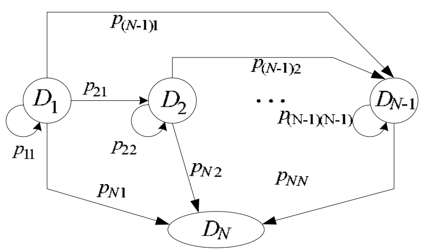

Figure 1. Transitions without any activities

To mitigate deterioration processes that may increase probabilities of being a failure in the future, maintenance activities are often employed. In this paper, it assumes that there can be N-1 types of maintenance activities, i.e., M_1, M_2,…,M_{N-1}, for a transformer with N states. For the maintenance activity M_m, it can make the state D_q ($1 \le q \le N$-1) return to the state D_1 when $m > q$. If $m \le q$, the maintenance activity M_m can make the state D_q ($1 \le q \le N$-1) return to the state D_{q-m+1}. Maintenance activities cannot change the fault state.

The repair activity, denoted as M_N, can make any operating states or the failure state return to the best state, i.e., D_1, in the next time interval.

For the transformer i with N states, the activity set can be denoted as

$$\Theta_A = \{M_0, M_1, \cdots, M_N\} \tag{1}$$

where M_0 means no activity on the transformer i.

The transition matrix can be written as

$$\boldsymbol{P}_{i,a} = [p_{jk}^{(i,a)}]_{N\times N} \tag{2}$$

where $\boldsymbol{P}_{i,a}$ is the transition matrix of the transformer i. When $a = 0$, it means the transition matrix corresponding to M_0. $a = 1,\cdots, N-1$ denote the maintenance activities M_1, …,M_{N-1} respectively and $a = N$ represents the repair activity. $p_{jk}^{(i,a)}$ is the transition probability of the transformer i from the state D_k to the state D_j with the activity $M_a (a = 0,\cdots N)$. Based on the transition matrices, the probability from one state to itself or another state with different activities can be easily obtained.

B. Deterioration Processes of Multiple Transformers

For n transformers, a state set and an activity set can be defined as follows.

$$\boldsymbol{\Pi}_t = \{s_{1,t}, \cdots, s_{i,t}, \cdots, s_{n,t}\} \tag{3}$$

$$\boldsymbol{\pi}_t = \{A_{1,t}, \cdots, A_{i,t}, \cdots, A_{n,t}\} \tag{4}$$

where $\boldsymbol{\Pi}_t$ is a state set of n transformers in the tth time interval, $s_{i,t} \in \Theta_D$ is the state of the transformer i in the tth time interval, $\boldsymbol{\pi}_t$ is an activity set of n transformers in the tth time interval, $A_{i,t} \in \Theta_A$ is the activity that is implemented on the transformer i in the tth time interval.

The probability from $\boldsymbol{\Pi}_t$ in the tth time interval to $\boldsymbol{\Pi}_{t+1}$ in the (t+1)th time interval with $\boldsymbol{\pi}_t$ can be described as

$$P(\boldsymbol{\Pi}_{t+1} \mid \boldsymbol{\Pi}_t, \boldsymbol{\pi}_t) = \prod_{i\in\Theta_T} P(s_{i,(t+1)} \mid s_{i,t}, A_{i,t}) \tag{5}$$

where Θ_T is the set of indices of transformers, $P(s_{i,(t+1)} \mid s_{i,t}, A_{i,t})$ is the probability of the transformer i from the state $s_{i,t}$ in the tth time interval to the state $s_{i,(t+1)}$ in the (t+1)th time interval with the activity $A_{i,t}$. These probabilities can be obtained according to the transition matrices.

III. A Dynamic Optimization Model

In this section, a model, considering current and successive influences with different operating conditions, is built to optimize coordinated maintenance activities dynamically. In this paper, there are following two assumptions:

- At most one transformer can be on maintenance in a time interval.
- Any transformers cannot be on maintenance if any other transformers are in the failure states.

A. The Expected Cost-to-go with All Components in Normal Operation

When all transformers are in normal operating states, there are many different maintenance strategies that can be implemented. Different strategies can result in different influences in the future. The expected cost-to-go, which means the total cost from the current time interval to the terminal time interval, can be employed to evaluate the influences caused by the implementation of a certain maintenance strategy. The expected cost-to-go with all transformers in normal operation includes the activity cost, the load loss cost and the successive cost caused by actions.

The activity cost $C_{A,t}$ of $\boldsymbol{\Pi}_t \subset \Theta_O$ with $\boldsymbol{\pi}_t \subset \Theta_{\boldsymbol{\pi}}$ can be denoted as

$$C_{A,t} = \sum_{i \in \Theta_T} CA_i(A_{i,t}) \tag{6}$$

where Θ_O is the set of all possible system state sets with all transformers in normal operating states, Θ_{π} is the set of all possible activity sets for $\boldsymbol{\Pi}_t$, $CA_i(A_{i,t})$ demotes the activity cost caused by implementing the activity $A_{i,t}$ on the transformer i.

The load loss cost $C_{L,t}$ is represented as

$$C_{L,t} = \sum_{i \in \Theta_T} CL_i(A_{i,t}) \tag{7}$$

where $CL_i(A_{i,t})$ denotes the load loss cost caused by implementing the activity $A_{i,t}$ on the transformer *i*. Because the transformer should be off line when on maintenance, there may be load losses with heavy loads.

Different activities on different transformers will results in different influences on the successive. The successive cost for $\boldsymbol{\Pi}_t \subset \Theta_O$ with $\boldsymbol{\pi}_t$ can be expressed as follows.

$$C_{S,t} = \sum_{\boldsymbol{\Pi}_{t+1} \subset \Theta_O \cup \Theta_F} \left[v^*_{t+1}(\boldsymbol{\Pi}_{t+1}) \cdot P(\boldsymbol{\Pi}_{t+1} \mid \boldsymbol{\Pi}_t, \boldsymbol{\pi}_t) \right] \tag{8}$$

where Θ_F is the set of all possible system state sets with different numbers of transformers in failure states. $v^*_{t+1}(\boldsymbol{\Pi}_{t+1})$ is the minimum expected cost-to-go with the state matrix $\boldsymbol{\Pi}_{t+1}$ in the (t+1)th time interval. The calculation of the minimum expected cost-to-go will be introduced in the next section.

Therefore, the expected cost-to-go with $\boldsymbol{\Pi}_t$ and $\boldsymbol{\pi}_t$ can be written as

$$v_t(\boldsymbol{\Pi}_t, \boldsymbol{\pi}_t) = C_{A,t} + C_{L,t} + C_{S,t} \tag{9}$$

B. The Minimum Expected Cost-to-go with All Components in Operation

For all components in normal operating states, i.e., $\boldsymbol{\Pi}_t \subset \Theta_O$, in the *t*th time interval, the minimum expected total cost-to-go can be shown as the equation (10).

$$v^*_t(\boldsymbol{\Pi}_t) = \min\left\{ v_t(\boldsymbol{\Pi}_t, \boldsymbol{\pi}_t), \boldsymbol{\pi}_t \subset \Theta_{\pi} \right\}, \quad \boldsymbol{\Pi}_t \subset \Theta_O \tag{10}$$

C. The Minimum Expected Cost-to-go with Components in Failure

When transformers in a power system are in the fault states, servicemen and auxiliary equipment should be arranged to fix the faults. However, servicemen and auxiliary equipment are not always ready-for-use. Therefore, this paper considers this factor. In this paper, it assumes that no maintenance activities are on any other non-fault transformers when any transformers are in the failure states.

Therefore, the activity set $\boldsymbol{\pi}_t^{(F)}$ for $\boldsymbol{\Pi}_t \subset \Theta_F$ can be easily determined. It can be shown as

$$\boldsymbol{\pi}_t^{(F)} = \{A_{1,t}^{(R)}, \cdots, A_{i,t}^{(R)}, \cdots, A_{n,t}^{(R)}\} \tag{11}$$

where $\boldsymbol{\pi}_t^{(R)}$ is an activity set, $A_{i,t}^{(R)}$ is a repair activity, i.e., M_N, when the corresponding transformer is in the fault state, or $A_{i,t}^{(R)}$ is M_0 when the corresponding transformer is in the normal operating state.

The minimum expected cost-to-go with components in the failure states can be denoted as

$$v^*_t(\boldsymbol{\Pi}_t) = v_t(\boldsymbol{\Pi}_t, \boldsymbol{\pi}_t^{(F)}) \tag{12}$$

The expected cost-to-go $v_t(\boldsymbol{\Pi}_t, \boldsymbol{\pi}_t^{(F)})$ of $\boldsymbol{\Pi}_t \subset \Theta_F$ with $\boldsymbol{\pi}_t^{(F)}$ includes three parts that are the load loss cost, the repair cost and the successive cost. It can be written as

$$v_t(\boldsymbol{\Pi}_t, \boldsymbol{\pi}_t^{(F)}) = CL_t^{(F)}(\boldsymbol{\Pi}_t) + CR_t(\boldsymbol{\pi}_t^{(F)}) + \sum_{\boldsymbol{\Pi}_{t+1} \subset \Theta_O \cup \Theta_F} \left[v^*_{t+1}(\boldsymbol{\Pi}_{t+1}) \cdot P(\boldsymbol{\Pi}_{t+1} \mid \boldsymbol{\Pi}_t, \boldsymbol{\pi}_t^{(F)}) \right] \tag{13}$$

where $CL_t^{(F)}(\boldsymbol{\Pi}_t)$ is the load loss cost with $\boldsymbol{\Pi}_t \subset \Theta_F$, $CR_t(\boldsymbol{\pi}_t^{(F)})$ is the repair cost under $\boldsymbol{\pi}_t^{(F)}$, the third term on the right of equation (5) is the successive cost for $\boldsymbol{\Pi}_t \subset \Theta_F$ with $\boldsymbol{\pi}_t^{(F)}$.

D. A Revised Backward Induction Algorithm

The backward induction algorithm is an efficient method to solve finite horizon discrete time Markov decision processes. In this paper, a searching space reduction method is used to speed up the calculation. With the increasing number of components, there will be a huge number of combinations of different conditions in a time interval. The calculations of probabilities from a certain condition in the *t*th time interval to all possible conditions in the (t+1)th time interval will be a time-consuming task. To reduce the amount of calculations, a searching space reduction method is employed. Empirically, the transition probability of a component from a certain condition to another deteriorated condition without any activities is often very small. Therefore, the probability, which the states of multiple components are deteriorated to worse simultaneously, is often so small that it can be ignored. Actually, we can consider at most three to five components whose states are deteriorated to worse states at the same time interval. This method can reduce the amount of calculation to a certain degree.

The detailed steps of solving the proposed model, considering *T* time intervals, are shown as follows:

Step 1) According to deteriorated processes of components, generate the sets Θ_O, Θ_F, and Θ_{π}.

Step 2) Repeat for t=T, T-1,…,1.

--Step 2.1) For $\boldsymbol{\Pi}_t \subset \Theta_O$, determine a possible strategy $\boldsymbol{\pi}_t \subset \Theta_\pi$. Compute the activity cost $C_{A,t}$, the load loss cost $C_{L,t}$, the successive cost $C_{S,t}$ and the expected cost-to-go according to the equations (6)~(9).

--Step 2.2) Compute all possible expected cost-to-goes for $\boldsymbol{\Pi}_t \subset \Theta_O$. The strategy with the minimum expected cost-to-go is the optimal strategy according to the equation (10).

--Step 2.3) For $\boldsymbol{\Pi}_t \subset \Theta_F$, determine the corresponding strategy $\boldsymbol{\pi}_t^{(F)}$ according to the equation (11).

--Step 2.4) Compute the minimum expected cost-to-go of $\boldsymbol{\Pi}_t \subset \Theta_F$ under $\boldsymbol{\pi}_t^{(F)}$ using the equations (12) and (13).

--Step 2.5) Set $t = t-1$, go back to Step 2.1). For the *T*th time interval, the successive costs are not considered.

IV. Case Study

In this section, an IEEE 30-bus system is presented to show that the proposed dynamic coordinated maintenance strategies are correctness and efficient. In this paper, we mainly focus on three states, i.e., a good state (D_1), a deteriorated state (D_2) and a fault state (D_3), for each transformer. D_1 and D_2 of transformers in actual operations can be provided by advanced sensors and monitoring units in intelligent substations.

Two maintenance activities, i.e., a minor maintenance activity (M_1) and a major maintenance (M_2), and a repair activity can be performed. *D*1 and *D*2 can retain the same state in the next time interval with *M*1. *D*1 can retain the same state and *D*2 can return to the state *D*1 with *M*2. In the simulation, 52 weeks, i.e., one year time horizon, and at most double faults are considered for the maintenance scheduling.

TABLE I shows maintenance costs and repair costs of different transformers. *T*1, *T*2, *T*3 and *T*4 represent transformers between bus6-bus10, bus6-bus9, bus27-bus28 and bus4-bus12 respectively in the IEEE 30-bus system. The load curve over 52 weeks is shown in Fig.2, with a week as one time interval.

TABLE I. Costs (10^4RMB) of Transformers

		*T*1	*T*2	*T*3	*T*4
*M*1	Case1	0.8	1.0	1.0	1.0
	Case2	1.0	0.8	0.7	1.0
*M*2	Case1	6.5	6.4	6.0	6.5
	Case2	6.5	6.4	6.0	6.5
Repair	Case1	12	15	16	15.5
	Case2	12	17	16	9

Fig.3 shows the optimal maintenance strategies with two different operating conditions of transformers over the whole time intervals. It dynamically provides optimal coordinated maintenance strategies according to the different conditions in each interval.

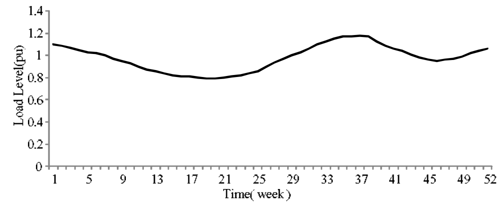

Figure 2. Load curve of one year

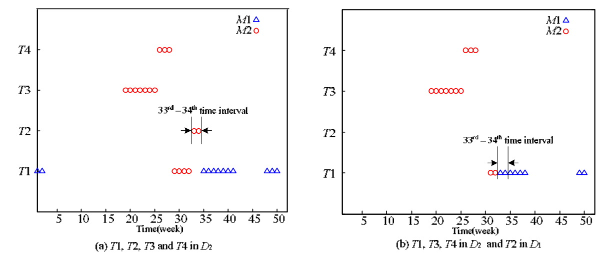

Figure 3. Strategies with different conditions over 52 time intervals

When operating conditions of transformers are different in a certain time interval, there will be different strategies accordingly. For example, if *T*1, *T*2, *T*3 and *T*4 are in D_2 in the 33rd or 34th time interval, the optimal strategy should be a major maintenance (*M*2) on *T*2, shown in Fig.3 (a). If *T*1, *T*3, *T*4 are in D_2 and *T*2 is in D_1 in the 33rd or 34th time interval, the optimal strategy should be a minor maintenance (*M*1) on *T*1, shown in Fig.3 (b).

Fig.3 (a) provides optimal strategies when *T*1, *T*2, *T*3 and *T*4 are in D_2 over different time intervals and Fig.3 (b) provides optimal strategies when *T*1, *T*3 and *T*4 are in D_2 and *T*2 is in D_1 over different time intervals.

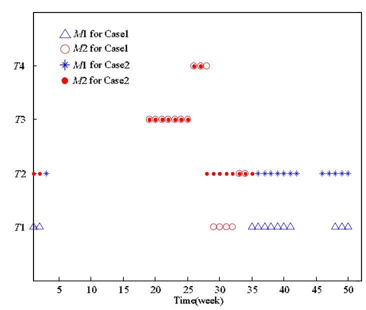

Figure 4. Optimal maintenance strategies for *T*1, *T*2, *T*3 and *T*4 in D_2

In the second case, some costs in the first case are changed. The optimal strategies when *T*1, *T*2, *T*3 and *T*4 are in D_2 in different time intervals are shown in Fig.4. Compared with the case 1, more minor maintenance activities will be implemented on *T*2 because the M_1 cost of *T*1 in the case 1 is higher and the M_1 cost of *T*2 in the case 2 is lower. In the case 2, the M_1 cost of *T*3 is also lower compared with that in the case 1, but a minor maintenance on *T*3 will result in larger load losses compared with that on *T*2. Therefore, minor maintenance activities are mainly implemented on *T*2 rather than on *T*3. This paper assumes that the load losses with different faults are calculated by OPF with the objective of minimizing load losses. The repair cost of *T*2 increases from

15 to 17, which may increase the successive cost caused by repair activities after faults on $T2$, therefore, more maintenance activities, compared with the case 1, are implemented on $T2$ in the case 2 to reduce potential repair costs in the future.

Considering the unrepaired probabilities caused by external factors, the third case analyzes influences of external factors on maintenance strategies. TABLE II shows unrepaired probabilities. Fig.5 shows the strategies with and without considering the unrepaired probabilities respectively. Time intervals circled by dot ellipses are different strategies caused by unrepaired probabilities. The results show that higher unrepaired probabilities, especially in summer and winter with higher load demands, will have a relatively great influence on optimal maintenance strategies.

TABLE II. UNREPAIRED PROBABILITIES OVER ALL TIME INTERVALS

Weeks	1 ~3	4 ~24	25 ~32	33 ~37	38 ~41	42 ~47	48 ~52
Unrepaired probability	0.15	0.05	0.1	0.22	0.05	0.1	0.20

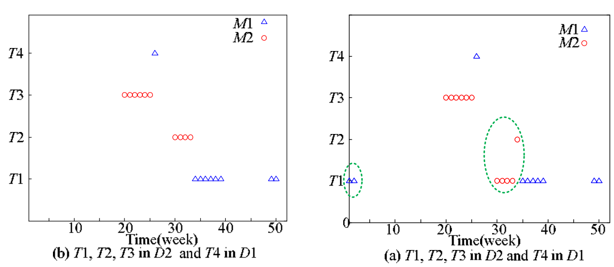

Figure 5. Optimal maintenance strategies for $T1$, $T2$, $T3$ and $T4$ in D_2

According to the above analysis, the proposed model is reasonable and it can provide operators with a series of dynamic coordinated maintenance strategies according to the different conditions of multiple transformers.

V. CONCLUSIONS

Based on accurate information about operating states of transformers provided by advanced sensors and monitoring units in intelligent substations, this paper proposes a dynamic model to provide maintenance strategies coordinately for multiple transformers. Firstly, an individual deterioration model and a multi-transformer deterioration model are built based on Markov processes. Secondly, an optimization model considering an expected cost-to-go, including load losses, maintenance costs and equivalent successive costs in the future is built. Unrepaired factors caused by bad weather conditions and unavailability of servicemen and auxiliary equipment are considered in the model to make maintenance strategies more realistic. A backward induction algorithm is employed to solve this model. A test system is employed to prove the proposed model corrective and the results show that optimal maintenance strategies can be adjusted according to the different operating conditions of multiple transformers.

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