Optimization of Condition-based Maintenance for Traction Power Supply Equipment based on Partially Observable Semi-Markov Decision Process

Ruidong Fan
School of Electrical Engineering
Southwest Jiaotong University
Chengdu, China
rdfan@foxmail.com

Ding Feng
School of Electrical Engineering
Southwest Jiaotong University
Chengdu, China
Fengding1990@163.com

Chao Yang
School of Electrical Engineering
Southwest Jiaotong University
Chengdu, China
yangchao919@163.com

Sheng Lin*
School of Electrical Engineering
Southwest Jiaotong University
Chengdu, China
slin@swjtu.edu.cn

***Abstract*—Due to uncertainty of state evaluation, the result of state evaluation may not be consistent with the actual state of the equipment. A maintenance scheme ignoring this uncertainty can cause additional downtime and economic costs. Aiming at this problem, a condition-based maintenance (CBM) model is established based on the partially observable Markov decision process (POMDP) which is continuous in time. The continuous-time Markov chain is used to describe the degradation process of traction power supply equipment (TPSE). The equipment state is classified into four levels and the transition probabilities between different states are solved. In order to quantify the uncertainty of state evaluation, the state-observation probability is introduced. Considering the maintenance cost and the failure risk, the optimal maintenance method and inspection period are determined based on this model. Finally, the recorded degradation data of 27.5-kV vacuum circuit breakers for a traction power supply system (TPSS) are used in the numerical example to illustrate the effectiveness of this model.**

Keywords—traction power supply equipment; partially observable semi-Markov decision process; state evaluation; condition-based maintenance

I. INTRODUCTION

The conventional schedule maintenance mode of traction power supply equipment (TPSE) has the shortcomings of heavy workload, poor pertinence, high cost and low efficiency [1]. It is urgently needed to improve the maintenance mode of TPSE. Condition-based maintenance (CBM) is a new development direction of maintenance mode and has received great interest in recent years [2-5]. Decision-making of CBM is based on the equipment state, which can avoid the insufficient maintenance and excessive maintenance.

However, the uncertainty of state evaluation is ignored in most existing researches. In practical, the actual state of the equipment is unlikely obtained accurately through state evaluation. Firstly, the errors in state data collection is inevitable. Then, the uncertainty in state evaluation model and algorithm also affects the accuracy of state evaluation. Therefore, the result of state evaluation may not be consistent with the actual state of the equipment. The uncertainty of state evaluation needs to be considered in maintenance scheme determination, thus avoiding decision mistakes caused by the uncertainty.

Partially observable Markov decision process (POMDP) is a commonly approach to performing maintenance decision-making based on the state evaluation result with uncertainty. Chen et al. [6] established a CBM model based on POMDP and only a limited number of imperfect maintenance actions can be performed in this model. In [7], the POMDP was used to model decision-making under uncertainty and the impact of measurement errors in the POMDP context is demonstrated. Papakonstantinou & Shinozuka [8] proposed a point-based value iteration algorithm to solve the POMDP model and evaluated its performance and solution quality.

It appears that existing applications of POMDP in maintenance optimization are mostly discrete in time. However, the transitions of equipment state and maintenance activities take a continuous period of time, not instantaneously at discrete epochs. In addition, the above researches only considered the optimization of economic cost, ignoring the failure risk of equipment after maintenance, which leads to poor effect of maintenance scheme and high failure rate of equipment after maintenance.

To address the limitations of current research, a CBM model based on POSMDP is developed in this paper. The residence time of each equipment state is considered and the state transition probabilities are time-varying. The state observation probability is used to quantify the uncertainty of state evaluation. To achieve the optimization of both economic cost and reliability, the failure risk of equipment after maintenance is quantified as a part of comprehensive cost. The recorded fault data of 27.5-kV vacuum circuit breakers for a TPSS are used to verify the model.

The remainder of this paper is organised as follows. Section II introduces the degradation process of equipment. Section III establishes the CBM model based on the POSMDP. Then a numerical example is provided to show the effectiveness of the model in Section IV. The last Section gives the conclusion of this paper.

This work was supported by the Scientific and Technological Research and Development Program of CHINA RAILWAY under grants N2018G023, and 2017J001-F.

II. DEGRADATION PROCESS OF TPSE

A. Transition process of equipment state

The continuous-time Markov chain is used to describe the degradation process of TPSE in this paper. The equipment state is classified into four levels, i.e., normal, attentive, abnormal, and failure. It is assumed that the residence time of each state follows an exponential distribution. The state transition process of TPSE is shown in Fig. 1.

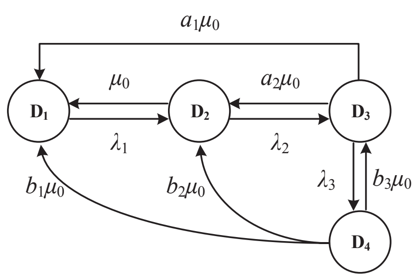

Figure 1. State transition process of TPSE

In Fig. 1, D_1-D_4 represent the four equipment states, i.e., normal, attentive, abnormal and failure states, respectively. No maintenance action is needed for equipment in normal state. Equipment in failure state is not operational and the failure state can be known without evaluation. λ_1, λ_2, λ_3 are the degradation rates and μ_0 is the repair rate. The maintenance in this paper is imperfect. a_i is the probability for the state of equipment to transfer from D_3 to D_i and b_i is the probability of equipment state transferring from D_4 to D_i. a_i and b_i satisfy the following conditions: $a_1+a_2=1$, $b_1+b_2+b_3=1$ [9]. The state transition rate matrix of four-state continuous-time Markov chain is as follows:

$$\boldsymbol{Q}=\begin{bmatrix}-\Sigma_1 & q_{12} & q_{13} & q_{14}\\ q_{21} & -\Sigma_2 & q_{23} & q_{24}\\ q_{31} & q_{32} & -\Sigma_3 & q_{34}\\ q_{41} & q_{42} & q_{43} & -\Sigma_4\end{bmatrix} \tag{1}$$

Where, q_{ij} is the transition rate of equipment state transferring from i to j. Σ_i is the sum of the non-diagonal elements in the i-th row.

B. State transition probability of TPSE

The probability of equipment state transferring from i to j after the time t is:

$$p_{ij}(t)=P\{X(t+u)=j\mid X(u)=i\}=q_{ij}t+\sigma(t) \tag{2}$$

where, u is the initial time of transition process, $\sigma(t)$ is a high order term of t. The probability that no state transition occurs is:

$$p_{ii}(t)=P\{X(t+u)=i\mid X(u)=i\}=1+q_{ii}t+\sigma(t) \tag{3}$$

According to the Kolmogorov equation:

$$\begin{aligned}&p_{ij}(t+\Delta t)\\&=\sum_{k\in\Omega}p_{ik}(t)p_{kj}(\Delta t)\\&=p_{ij}(t)p_{jj}(\Delta t)+\sum_{\substack{k\in\Omega\\k\neq j}}p_{ik}(t)p_{kj}(\Delta t)\\&=p_{ij}(t)\left(1+q_{jj}\Delta t+\sigma(\Delta t)\right)+\sum_{\substack{k\in\Omega\\k\neq j}}p_{ik}(t)\left(q_{kj}\Delta t+\sigma(\Delta t)\right)\end{aligned} \tag{4}$$

The following equation can be obtained according to (4):

$$\lim_{\Delta t\to 0}\frac{p_{ij}(t+\Delta t)-p_{ij}(t)}{\Delta t}=\sum_{k\in\Omega}p_{ik}(t)\lim_{\Delta t\to 0}\left(q_{kj}+\frac{\sigma(\Delta t)}{\Delta t}\right) \tag{5}$$

The above equation can be written in the following form:

$$p'_{ij}(t)=\sum_{k\in\Omega}p_{ik}(t)q_{kj} \tag{6}$$

Thus, the state transition probability of n-state Markov chain satisfies the following equation:

$$\begin{bmatrix}p'_{11}(t) & p'_{12}(t) & \cdots & p'_{1n}(t)\\ p'_{21}(t) & p'_{22}(t) & \cdots & p'_{2n}(t)\\ \vdots & \vdots & \ddots & \vdots\\ p'_{n1}(t) & p'_{n2}(t) & \cdots & p'_{nn}(t)\end{bmatrix}=\begin{bmatrix}p_{11}(t) & p_{12}(t) & \cdots & p_{1n}(t)\\ p_{21}(t) & p_{22}(t) & \cdots & p_{2n}(t)\\ \vdots & \vdots & \ddots & \vdots\\ p_{n1}(t) & p_{n2}(t) & \cdots & p_{nn}(t)\end{bmatrix}\begin{bmatrix}q_{11} & q_{12} & \cdots & q_{1n}\\ q_{21} & q_{22} & \cdots & q_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ q_{n1} & q_{n2} & \cdots & q_{nn}\end{bmatrix} \tag{7}$$

The state transition probability can be obtained by substituting the state transition rate matrix into (5) and solving it.

III. CONDITION-BASED MAINTENANCE MODEL BASED ON POSMDP

A. Theory of POSMDP

Partially observable Markov decision process (POSMDP) is the extension of Markov decision process and is introduced for maintenance modeling in this paper. POSMDP can be described with a 7-point group:

$$\{S,Z,A,p_{ij}(t,a),o_{jk},\tau(i,a),r(i,a),i\in S,j\in S,k\in Z\}$$

The meaning of each variable is as follows:

(1) S is the set of equipment states. $S=\{1,2,3,4\}$ and 1-4 represent the four equipment states, i.e., normal, attentive, abnormal and failure states, respectively.

(2) Z is the set of observation states. $Z=\{1,2,3,4\}$ and 1-4 represent the four results of state evaluation, i.e., normal, attentive, abnormal and failure states, respectively.

(3) A is the set of maintenance actions. Four maintenance actions are considered in this paper. $A=\{1,2,3,4\}$ and 1-4 represent the four maintenance actions, i.e., no maintenance, preventive maintenance, replacement and corrective maintenance, respectively. The definitions of four maintenance actions and corresponding state transition rate matrices are as follows:

a) No maintenance: No maintenance action is performed, the equipment will degrade naturally until the next inspection epoch. The state transition rate matrix is shown below.

$$\boldsymbol{Q}_1=\begin{bmatrix} -\lambda_1 & \lambda_1 & 0 & 0 \\ 0 & -\lambda_2 & \lambda_2 & 0 \\ 0 & 0 & -\lambda_3 & \lambda_3 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{8}$$

b) Preventive maintenance: Maintenance for improving the state of equipment when the equipment is in the state of attentive or abnormal. The values of a_i are as follows: $a_1=0.3$ and $a_2=0.7$. The state transition rate matrix is shown below.

$$\boldsymbol{Q}_2=\begin{bmatrix} 0 & 0 & 0 & 0 \\ \mu_0 & -\mu_0 & 0 & 0 \\ 0.3\mu_0 & 0.7\mu_0 & -\mu_0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{9}$$

c) Replacement: Overall replacement of equipment. The new equipment is in normal state. After replacement, the equipment will degrade naturally until the next inspection epoch. The state transition rate matrix is shown below.

$$\boldsymbol{Q}_3=\begin{bmatrix} -\lambda_1 & \lambda_1 & 0 & 0 \\ 0 & -\lambda_2 & \lambda_2 & 0 \\ 0 & 0 & -\lambda_3 & \lambda_3 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{10}$$

d) Corrective maintenance: Emergency maintenance of equipment when it fails to operate. The values of b_i are as follows: $b_1=0.1$, $b_2=0.3$ and $b_3=0.6$. The state transition rate matrix is shown below.

$$\boldsymbol{Q}_4=\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0.1\mu_0 & 0.3\mu_0 & 0.6\mu_0 & -\mu_0 \end{bmatrix} \tag{11}$$

(4) $p_{ij}(t,a)$ is the probability of equipment state transferring to j after the time t, given current state i and maintenance action a. By substituting the state transition rate matrix $\boldsymbol{Q}_i$ into (7), the state transition probability corresponding to four maintenance actions can be obtained.

$$p_{ij}(t,a)=\begin{cases} p_{ij}(t,1) & a=1 \\ \sum\limits_{l\in S,l>i} p_{il}(t_{PM},2)p_{lj}(t,1) & a=2 \\ p_{1j}(t,1) & a=3 \\ \sum\limits_{l\in S,l>4} p_{4l}(t_{CM},4)p_{lj}(t,1) & a=4 \end{cases} \tag{12}$$

Where, t_{PM} is the time required to take preventive maintenance and $t_{PM}=\int_0^\infty (1-F_{PM}(i,t))dt$. $F_{PM}(i,t)$ is the probability distribution of the time required for preventive maintenance when the equipment state is i. t_{CM} is the time required to take corrective maintenance. After the equipment is replaced, the new equipment is in normal state. Thus state transition probability after replacement is performed is $p_{ij}(t,3)=p_{1j}(t,1)$.

(5) o_{jk} is the probability that the state evaluation result is k when the actual state of equipment is j. The state observation probability matrix is shown as:

$$\boldsymbol{O}=\begin{bmatrix} 0.90 & 0.10 & 0 & 0 \\ 0.15 & 0.8 & 0.05 & 0 \\ 0 & 0.20 & 0.8 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{13}$$

(6) $\tau(i,a,T)$ is the transition time from the completion of maintenance actions to the end of the inspection cycle T, given current state i and action a. The transition time after the maintenance action is performed is shown as:

$$\tau(i,a,T)=\begin{cases} t_{IN}+T & a=1 \\ t_{IN}+t_{PM}+T & a=2 \\ t_{IN}+t_{RE}+T & a=3 \\ t_{CM}+T & a=4 \end{cases} \tag{14}$$

Where, t_{IN} is the time required for state detection and evaluation of equipment. t_{RE} is the time required to replace the equipment.

(7) $r(i,a,T)$ is the comprehensive cost, given the current state i, maintenance action a and inspection cycle T. The comprehensive cost is assigned as follows:

$$r_1(i,a,T)=\begin{cases} C_{IN}+C_d t_{IN}+C_{OP}(i)T & a=1 \\ C_{IN}+C_{PM}+C_d(t_{IN}+t_{PM}) \\ \quad +\sum\limits_{j\in S,j\neq 4} p_{ij}(t_{PM},2)C_{OP}(j)T & a=2 \\ C_{IN}+C_{RE}+C_d(t_{IN}+t_{RE})+C_{OP}(1)T & a=3 \\ C_{IN}+C_{CM}+C_d(t_{IN}+t_{CM}) \\ \quad +\sum\limits_{j\in S,j\neq 4} p_{ij}(t_{CM},4)C_{OP}(j)T & a=4 \end{cases} \tag{15}$$

Where, $r_1(i,a,T)$ is the basic cost, C_{IN} is the inspection cost, C_{PM} is the cost of preventive maintenance, C_{RE} is the cost of replacement, C_{CM} is the cost of corrective maintenance, C_d is the cost per unit time of downtime, $C_{OP}(i)$ is the operating cost per unit time when the equipment state is *i*. The equipment after maintenance also has the possibility of failure. In order to reduce the failure rate of equipment after maintenance and improve the effect of maintenance scheme, the failure risk of equipment after maintenance is quantified as economic cost.

$$r_2(i,a,T)=(C_{CM}+C_d t_{CM})\int_0^T p_{i4}(t,a)dt \tag{16}$$

Where, $r_2(i,a,T)$ is the failure risk cost of equipment after maintenance, given current state *i*, maintenance action *a* and inspection cycle *T*. The comprehensive cost is the sum of the basic cost and the failure risk cost:

$$r(i,a,T)=r_1(i,a,T)+r_2(i,a,T) \tag{17}$$

B. Condition-based maintenance decision process

Considering the uncertainty of state evaluation, the equipment state is expressed as a probability distribution called belief state. The belief state of equipment is denoted as $\boldsymbol{B}=[b(1),b(2),b(3),b(4)]$. $b(i)$ is the probability that the equipment state is *i*. $0\le b(i)\le 1$ and $\sum_{i\in S} b(i)=1$. The belief state of equipment at *m*-th inspection epoch is $\boldsymbol{B}_m=[b_m(1),b_m(2),b_m(3),b_m(4)]$ and the elements of $\boldsymbol{B}_m$ can be obtained according to the following equation [10]:

$$b_m(j)=\frac{o_{jk_m}\sum_{i\in S} p_{ij}(T,a)b_{m-1}(i)}{\sum_{j\in S} o_{jk_m}\sum_{i\in S} p_{ij}(T,a)b_{m-1}(i)} \tag{18}$$

The decision process of CBM considering the uncertainty of state evaluation is shown in Fig. 2. The state evaluation result at *m*-th inspection epoch is k_m , and then the belief state of equipment $\boldsymbol{B}_m$ can be solved according to (18). Finally, the optimal maintenance action a_m and inspection cycle T_m can be determined based on the belief state. The state of equipment will change after maintenance action is performed and the next maintenance decision will occur at the next inspection epoch.

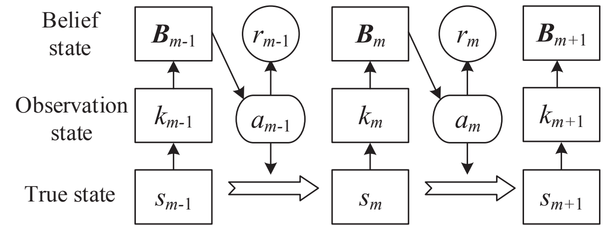

Figure 2. Maintenance decision process

C. Objective fuction

The POSMDP model can be transformed into POMDP model for solving it easier. From (14), we can see that there must be a normal number λ , which satisfies the following condition: $\lambda=\sup_{i\in S}\{\tau^{-1}(i,a,T)\}<+\infty$. Define the variable $\tau=1/\lambda$ The state transition probability and comprehensive cost are transformed as follows:

$$\begin{cases}\tilde{p}_{ij}(T,a)=\dfrac{\tau}{\tau(i,a,T)}[p_{ij}(T,a)-\delta_{ij}]+\delta_{ij}\\ \tilde{r}(i,a,T)=\dfrac{r(i,a,T)}{\tau(i,a,T)}\end{cases} \tag{19}$$

Where, $\delta_{ij}=\begin{cases}1, & i=j\\ 0, & i\neq j\end{cases}$, and $i,j\in S$. According to the principle of POMDP, the objective function of the condition-based maintenance model is constructed as follows:

$$V_n(\boldsymbol{B},T)=\min_{a\in A}\left\{\sum_{i\in S} b(i)[\tilde{r}(i,a,T)+\sum_{k\in Z}\sum_{j\in S} o_{jk}\,\tilde{p}_{ij}(T,a)V_{n-1}(\boldsymbol{B}^{a,k},T)]\right\} \tag{20}$$

Where, $V_n(\boldsymbol{B},T)$ is the optimal comprehensive cost of step *n* in the iteration, given current belief state $\boldsymbol{B}$ and inspection cycle T . $\boldsymbol{B}^{a,k}$ is the belief state at the next inspection epoch, given current belief state $\boldsymbol{B}$ and observation state at next inspection epoch *k*. The required objective function can be obtained by substituting (19) into (20):

$$V_n(\boldsymbol{B},T)=\min_{a\in A}\left\{\sum_{i\in S} b(i)[\frac{r(i,a,T)}{\tau(i,a,T)}+\frac{\tau}{\tau(i,a,T)}\sum_{k\in Z}\sum_{j\in S} o_{jk}p_{ij}(T,a)V_{n-1}(\boldsymbol{B}^{a,k},T)+(1-\frac{\tau}{\tau(i,a,T)})\sum_{k\in Z} o_{ik}V_{n-1}(\boldsymbol{B}^{a,k},T)]\right\} \tag{21}$$

D. Solution algorithm

The Perseus algorithm is used to solve the condition-based model in this paper. The steps of algorithm are as follows:

(1) Select the initial belief state $\boldsymbol{B}_0$ to establish a set of belief states $\boldsymbol{\Pi}=\{\boldsymbol{B}_0\}$. New belief states are calculated according to (18) with random maintenance actions are selected. Add the new belief states into $\boldsymbol{\Pi}$ until the upper limit of the number h is reached. Then the set of belief states can be obtained: $\boldsymbol{\Pi}=\{\boldsymbol{B}_0,\boldsymbol{B}_1,\cdots,\boldsymbol{B}_h\}$.

(2) Solve the initial comprehensive cost of each belief state: $V_0(\boldsymbol{B},T)=\min_{a\in A}[\sum_{i\in S} b(i)\dfrac{r(i,a,T)}{\tau(i,a,T)}]$.

(3) According to (22), the comprehensive cost iteration is carried out for each belief state in the set of belief states until the following condition is met: $|V_n(\boldsymbol{B},T)-V_{n-1}(\boldsymbol{B},T)|\le\varepsilon$, where ε is any positive number. By the end of the iteration, the optimal comprehensive cost can be obtained: $V^*(\boldsymbol{B},T)=V_n(\boldsymbol{B},T)$. The maintenance action a and the inspection cycle T corresponding to $V_n(\boldsymbol{B},T)$ are the optimal solutions.

IV. Numerical Illustration

The recorded fault data of 27.5-kV vacuum circuit breakers for a TPSS are used to verify the model. The degradation rates of 27.5-kV vacuum circuit breakers are $\lambda_1=0.0005$, $\lambda_2=0.0014$, $\lambda_3=0.0022$. The repair rate is $\mu_0=0.5$. The time required to take inspection is $t_{IN}=0.5\text{d}$, the time required to replace the equipment is $t_{RE}=1.5\text{d}$, and the time required to take corrective maintenance is $t_{CM}=2\text{d}$. The time required for preventive maintenance is related to the state of the equipment. The probability distribution of the time required for preventive maintenance meets the following condition: $F_{PM}(i,t)=u(t-t_i)$, where $i=2,3$, $t_2=1\text{d}$, and $t_2=1.5\text{d}$. The costs of maintenance and inspection are shown in the TABLE I:

TABLE I. Maintenance Cost

State	Maintenance Cost				Inspection cost
	a=1	*a*=2	*a*=3	*a*=4	
S=1	0	-	39300	-	300
S=2	0	5100	39300	-	300
S=3	0	6030	39300	-	300
S=4	0	-	39300	10570	300

The operating cost of equipment in each state of the equipment are shown in TABLE II:

TABLE II. Operation Cost and Downtime Loss

State	Operating Cost	Downtime Loss
S=1	40	10700
S=2	60	10700
S=3	100	10700
S=4	150	10700

A. The optimal maintenance schemes of different initial belief state

The probability that the next observation state is k when the current belief state is $\boldsymbol{B}$ and the maintenance action a is performed can be obtained as:

$$\Pr(k\,|\,\boldsymbol{B},a)=\sum_{j\in S}o_{jk}\sum_{i\in S}p_{ij}(T,a)b(i) \tag{22}$$

When the state of the 27.5-kV vacuum circuit breaker is normal, attentive, abnormal and failure, the corresponding belief states are [1,0,0,0], [0,1,0,0], [0,0,1,0], and [0,0,0,1], respectively. In turn, the four belief states mentioned above are regarded as the belief states of equipment at 1st inspection epoch. Then optimal maintenance action can be determined. The probability of each observation state at the next inspection epoch can be calculated using (22), and the observation state with the highest probability is used to represent the state evaluation result at the next inspection epoch. The belief state at the next inspection epoch can be obtained according to (18) after the optimal maintenance action at current inspection epoch and the observation state at the next inspection epoch are known. After that, the next maintenance decision will be performed based on the next belief state. The results are shown in Fig. 3.

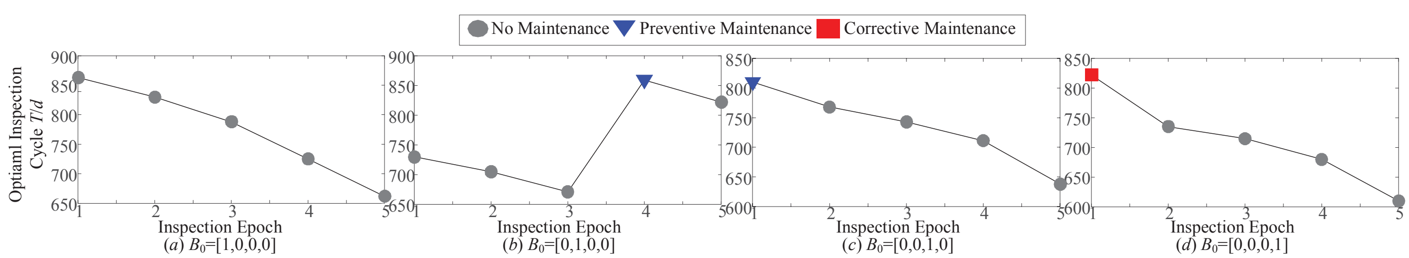

Figure 3. The optimal maintenance schemes at each inspection epoch

(1) When the belief state at the 1st inspection epoch is [1,0,0,0], no maintenance action is taken at the first five inspection epochs. However, as the equipment state becomes worse gradually, the risk of failure increases and the optimal inspection cycle decreases accordingly.

(2) When the belief state at the 1st inspection epoch is [0,1,0,0], the preventive maintenance is performed at the 4th inspection epoch. The failure risk increases as the deterioration of equipment, thereby the preventive maintenance is needed to prevent the equipment failure.

(3) When the belief state at the 1st inspection epoch is [0,0,1,0], the equipment is in a poor condition with a high failure rate. Therefore, preventive maintenance of equipment should be carried out immediately.

(4) When the belief state at the 1st inspection epoch is [0,0,0,1], the equipment is in the state of failure and is unable

to run. Corrective maintenance is needed to be performed to restore the operation of equipment.

B. The impact of maintenance effect on the optimal maintenance scheme

The service time and the number of times the equipment has been repaired have an impact on the improvement effect of of the equipment state after maintenance. Equipment with a long service life often has undergone much more times of maintenance, and the maintenance effect achieved by adopting the same maintenance action for such equipment is relatively poor. In order to analyze the influence of maintenance effect on the optimal maintenance scheme, two cases with different maintenance effect are proposed:

(1) Case 1: a_1=0.3, a_2=0.7, b_1=0.1, b_2=0.3, b_3=0.6.

(2) Case 2: a_1=0.1, a_2=0.9, b_1=0.01, b_2=0.04, b_3=0.9.

Taking [0,0,0,1] as the belief state at 1st inpection epoch, the maintenance schemes are optimized and the results are shown in Fig. 4.

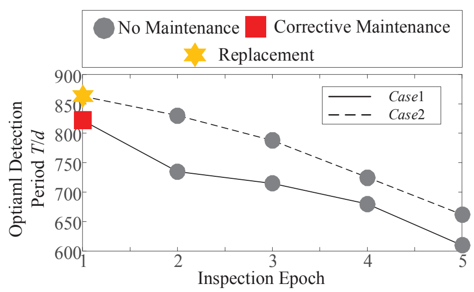

Figure 4. The optimal maintenance schemes corresponding to different mainteance effect

As can be seen from Fig. 4, the optimal maintenance action at 1st inspection epoch is replacement when the effect of maintenance is poorer. The failure risk of equipment after maintenance is much higher when the maintenance effect is poorer. Due to the high failure risk cost, the comprehensive cost of performing corrective maintenance is higher than that of replacing the equipment.

V. CONCLUSION

In order to optimize the maintenance under uncertainty, a condition-based maintenance model based on the POSMDP is proposed in this paper. The degradation process of equipment is described using a continuous-time Markov chain and the time-varying probability of state transition is calculated. The uncertainty of state evaluation is quantified using state observation probability. The failure risk of equipment after maintenance is considered when performing the optimization. The recorded fault data of 27.5-kV vaccum circuit breakers are used in the numerical example, and the following conclusions can be obtained.

(1) The state transition process is continuous in time and the state transition probability is time-varying, which is is consistent with the actual situation.

(2) With the increase of service time and maintenance times, the effect of maintenance on the improvement of equipment state is getting worse. Comparing the optimal maintenance schemes of equipment under different maintenance effects, we can see that this model can reduce the high failure risk caused by the poor effect of maintenance.

REFERENCES

[1] S. Lin, D. Feng and X. Sun, "Traction Power-Supply System Risk Assessment for High-Speed Railways Considering Train Timetable Effects," *IEEE Trans. Rel.*, vol. 68, pp. 1-9, 2018.

[2] D. Feng, S. Lin, Z. He, X. Sun and W. Lee, "Optimization Method with Prediction-based Maintenance Strategy for Traction Power Supply Equipment Based on Risk Quantification," *IEEE Trans. Transport. Electrific.,* vol. 4, no. 4, pp. 961 - 970, Dec. 2018.

[3] A. Zhang, S. Lin, D. Feng and Z. He, "Maintenance Decision-making Model Based on Markov Process For Traction Power Supply Equipment and Its Application," *J. China Railw. Soc*., vol.39, no.11, pp. 38-45, Nov. 2017.

[4] Q. Wang, Z. He, S. Lin and Z. Li, "Failure Modeling and Maintenance Decision for GIS Equipment Subject to Degradation and Shocks," *IEEE Trans. Power. Del.*, vol. 32, no. 2, pp. 1079-1088, Apr. 2017.

[5] Q. Wang, Z. He, S. Lin and Y. Liu, "Availability and Maintenance Modeling for GIS Equipment Served in High-Speed Railway under incomplete Maintenance," *IEEE Trans. Power. Del.*, vol. 33, no. 5, pp. 2143-2151, Oct. 2018.

[6] M. Y. Chen, H. D. Fan, C. H. Hu and D. H. Zhou "Maintaining Partially Observed Systems With Imperfect Observation and Resource Constraint," *IEEE Trans. Rel.*, vol. 63, no. 4, pp. 881-890, Dec. 2014.

[7] M. AlDurgam, and S. O. Duffuaa, " Optimal Maintenance Policies for Three-States POMDP with Quality Measurement Errors," IEEE International Conference on Industrial Engineering & Engineering Management., 2010.

[8] K. G. Papakonstantinou and M. Shinozuka, "Planning structural inspection and maintenance policies via dynamic programming and Markov processes. Part I: Theory," Reliability Engineering & System Safety, vol.130, pp. 202-213, Apr. 2014.

[9] K. G. Papakonstantinou and M. Shinozuka, "Planning structural inspection and maintenance policies via dynamic programming and Markov processes. Part II: POMDP implementation," Reliability Engineering & System Safety, vol.130, pp. 214-224, Apr. 2014.

[10] R. Srinivasan and A. K. Parlikad, "Semi-Markov Decision Process With Partial Information for Maintenance Decisions," *IEEE Trans. Rel.*, vol. 63, no. 4, pp. 891-898, Dec. 2014.