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Presenting Comprehensive Algorithm for Long Term Scheduling of Preventive Maintenance in the Electric Transmission Networks

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Abstract
One of the main challenges in preventive maintenance scheduling in electric transmission network is obtaining the model which can evaluates the effect of the maintenance and inspection strategies on the component reliability. Such model, on one hand, should be able to consider the uncertainties of components deterioration and, on the other hand, should consider the effect of maintenance and inspection strategies on the deterioration. In this paper, using Markov model, six maintenance models are extracted. These models help us to determine the best maintenance strategy for each failure mode.

Keywords: preventive maintenance, reliability, Markov model, failure mode

1. INTRODUCTION

Transmission maintenance networks scheduling is an optimization problem with complex constraints and the output depending on the time steps and the chosen time horizon. So, it can be divided into three categories of long-term, mid-term and short-term maintenance scheduling methods [1].

The objective of long term maintenance scheduling is to maximize the residual life of equipment while minimizing the cost of inspection ،repair and replacement. By the reason of long-term nature of components deterioration and since the effects of repairs and inspections appear over long time horizon, the output is just recommended long maintenance and inspection interval for components and it does not consider load, network structure, contracts, electricity prices and their changes. This information will be used in short-term and mid-term transmission maintenance scheduling. This is because for the long-term time frame, it is difficult to get accurate forecast. There are multiple constraints which will affect the result of long-term maintenance scheduling such as load, network structure, contracts, and electricity prices. So, maintenance scheduling is based on estimates.

Preventive maintenance strategies may be further divided into two different types: time based maintenance (TBM), condition based maintenance (CBM). TBM is usually a conservative (and costly) approach, whereby inspections and maintenance are performed at fixed time intervals**,** often, but not necessarily, based on history of the components and experience of the maintenance personnel. CBM triggers maintenance

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from information characterizing the equipment condition, since condition monitoring may identify incipient failures. If the amount of components deterioration exceeds a certain level, preventive maintenance is being carried out. Therefore, the long-term CBM scheduling output is the inspection time.

In long-term maintenance scheduling, developing model is the first major step to determine remaining life (equipment reliability) and inspection rate. An essential part of modelling maintenance is taking account of the uncertainties in the deterioration which represents the effect of inspections and maintenance on the deterioration.

Since Markov models are a kind of statistical models which are able to model these uncertainties, they are mainly used in Long-term maintenance scheduling. The procedure is based on the experience and the information about equipment operating history to determine deterioration function. The number of states in Markov model is calculated by deterioration function (in such a way that it represents the behavior of equipment deterioration). The basic assumption in the Markov model is that the transition from a failure state to another failure state follows an exponential distribution.

At first, Markov models were used for analyzing maintenance with periodic inspections [2], [4]. Then, by changing the perspective on periodic inspections (increasing the number of inspections due to the high degree of deterioration), these models were used to analyzing maintenance with non-periodic inspections. In [5], the maintenance model with non-periodic inspections for power switch is proposed. In [6], this model has been used to design strategic asset management. In [7], Markov model has been used for maintenance and inspections of oil-immersed transformer, and in [8], it has been suggested that, in order to have an optimal maintenance strategy in which the rates of inspections should be increased due to the high degree of deterioration. Also, [9], [10] approved the policy of increasing the rate of inspections appropriate to the level of depreciation by investigating the optimal maintenance strategy for power switch.

The nature of the transmission equipment failure could be divided into smaller modes under the heading of "failure modes". Due to the categorization, scheduling has more precise solutions for each mode. By determining the failure modes for each equipment, the maintenance scheduling is more precise. This made it reliable and easy to repair by maintenance team. Since it can be precisely treat failures for each mode.

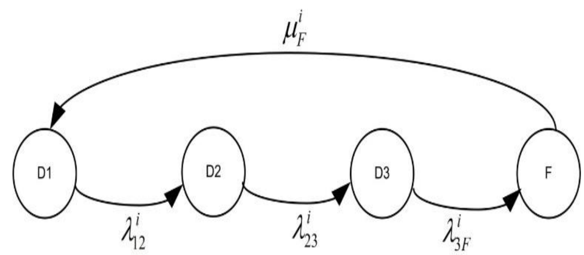

Fig. 1. Markov model with 4 states for i-th failure mode

Fig. 1. illustrates the classical Markov model with four states for i-th failure mode. As can be seen in Fig. 1, the deterioration process is modeled by four modes D_1, D_2, D_3 and F, which respectively represent normal failure, slight failure, major failure, and complete failure states of model. λ_{12}, λ_{23} and λ_{3F} are deterioration rates. The main problem of the model is that, it is assumed that the equipment state is always apparent to the user (e.g. by online monitoring). So, the equipment state is independent of the inspection and the inspections output must be led to repair. However, the equipment state is not obvious in practice and it is determined based on the inspections output.

Therefore, the definition of each state in practical applications model, will be subordinated to inspection and it is impossible to determine the equipment state without performing an inspection. For example, in the failure mode of insulation surface degradation of transformer, the failure mode of Markov model corresponds to the amount of dissolved gas in oil in the Oil-immersed transformer. Therefore, in order to determine the transformer state, the amount of dissolved gas in oil of transformer must be determined by the Dissolved Gas Analysis (DGA) test at first, and then the transformer state is determined according to the test information.

In [11] this problem is well-designed by combining the failure model and our understanding about the equipment based on combined Markov model. In the following, combined Markov models corresponding to minor and major maintenance are presented based on the Markov model. The minor maintenance is a kind of maintenance that improves the equipment to previous stage, but in the case of major maintenance, it improves the equipment to many previous stage as possible.

2. Condition based maintenance using Markov models:

There are four different maintenance types for CBM:

- Minor maintenance of D_2 and D_3, known as CBM1.
- Minor maintenance of D_3 and non-maintenance of D_2, known as CBM2.
- Major maintenance of D_3 and non-maintenance of D_2, known as CBM3.
- Minor maintenance of D_2 and major maintenance of D_3, known as CBM4.

In this categorization, some states are not considered as a permissible maintenance state. For example, the minor maintenance state in D_2 and non-maintenance of D_3 are not considered for possible scenarios, since it would not be reasonable to maintenance the D_2 mode and leave the D_3 mode, where the state of the mode worsened. In the following four maintenance types for CBM will be considered.

a.Minor maintenance of D_2 and D_3 (CBM1)

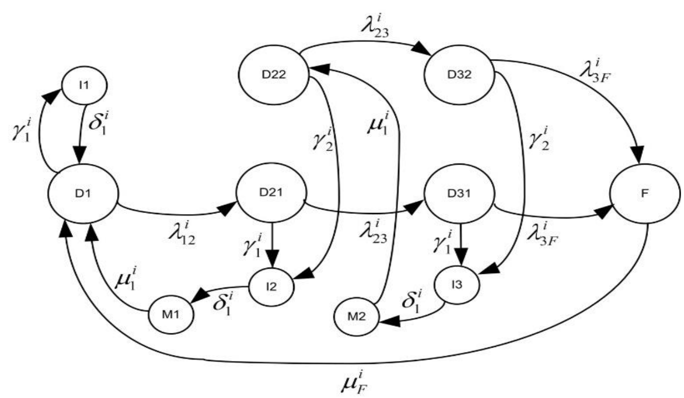

Fig. 2. Markov model with minor maintenance of D_2 and D_3

As shown in Fig. 2, two new modes, D_{22} and D_{32}, are added to the failure modes, which is modeling our knowledge about the equipment state. The definition of the states in Fig. 2:

D_1: The failure mode is in state 1, and we also know that the failure mode is in state 1.

D_{21}: The failure mode enters state 2 while we still think the failure mode is in state 1.

D_{31}: The failure mode enters state 3 while we still think the failure mode is in state 1.

D22: The failure mode enters state 2, and we also know that the failure mode is in state 2.

D_{32}: The failure mode enters state 3 while we still think the failure mode is in state 2.

In this model, it is assumed that the failure mode is in state 1 and its inspection rate is γ_1, and if the failure mode is in state 2 (minor failure), its inspection rate is γ_2. In D_1 mode, we know that the mode under study is in the intact state and its inspection rate is γ_1, and after confirmation that the failure mode is in the intact state (being in D_1 mode), repair operation is not performed by the inspection operators (mode I_1), and the output of I_1 mode will be back straight to the D_1 mode. In this case, the time of being in I_1 mode is $1/\delta_1$, which is the time to do the inspection.

It should be noted that if the inspection is done online, I_1 mode will be omitted. Similarly, when the failure mode is in D_{21} mode, actually the mode enters into minor fault condition while we still think it is in intact state (D_1). So, the inspection rate is γ_1 and after checking the inspection result (output of I_2 mode), which indicates that the equipment is in a failure mode, repair operations are performed (M_1 mode).

Because of the minor repairs, it goes back to the previous mode and the mode enters into D_1 mode. It is assumed that minor repairs will take $1/\mu_1$. The same goes for the case when the equipment is in D_{22} mode, the inspection rate is γ_2 because we know that the mode enters into minor fault condition and then to be continued as before. The same applies to the D_{31} and D_{32} modes, except that after minor repairs of these modes, the failure mode goes back to the previous mode, which is equivalent to D_{22}, because after the repair of the D_{31} and D_{32} mode, we know that the failure mode entered the main failure mode (D_2), and our knowledge about the D_2mode condition would be equivalent to the D_{22} mode.

b.Minor maintenance of D_3 and non-maintenance of D_2 (CBM2)

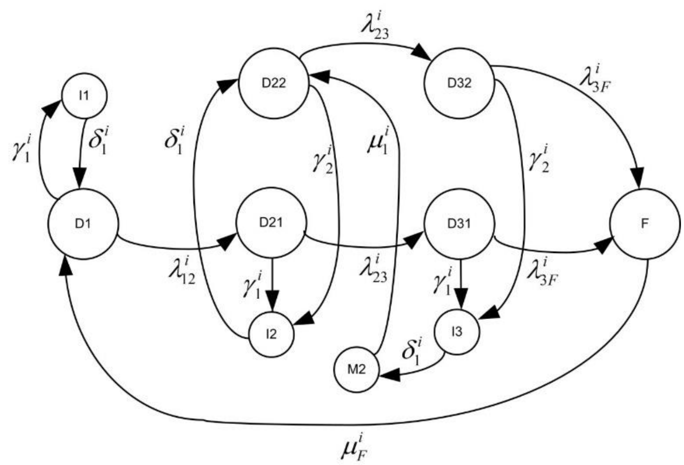

Fig. 3. . Markov model with minor maintenance of D_3 and non-maintenance of D_2

In the Markov model of Fig. 3, the inspection output of D_{21} and D_{22} modes goes back to D_{22}, which intricate that the repair is not done in this case.

c. Major maintenance of D_3 and non-maintenance of D_2 (CBM3)

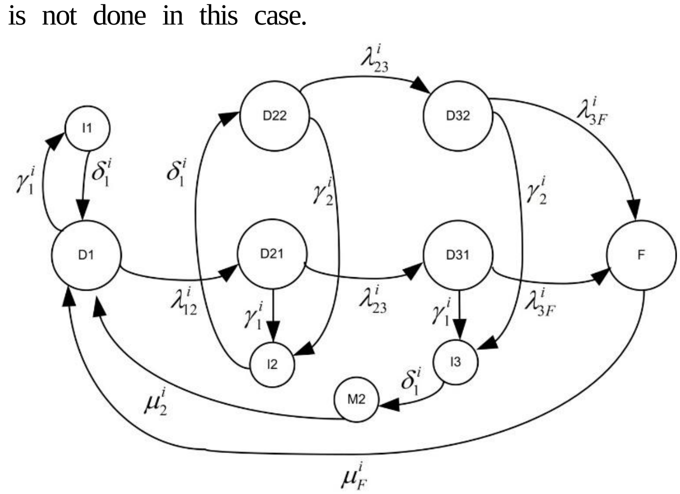

Fig. 4. Markov model with major maintenance of D_3 and non-maintenance of D_2

As shown in Fig. 4, the output of the inspections of stage 3 leads to a major repair (M_2 mode), which causes the failure mode to go back to D_1 mode.

d. Major maintenance of D_3 and minor maintenance of D_2 (CBM4)

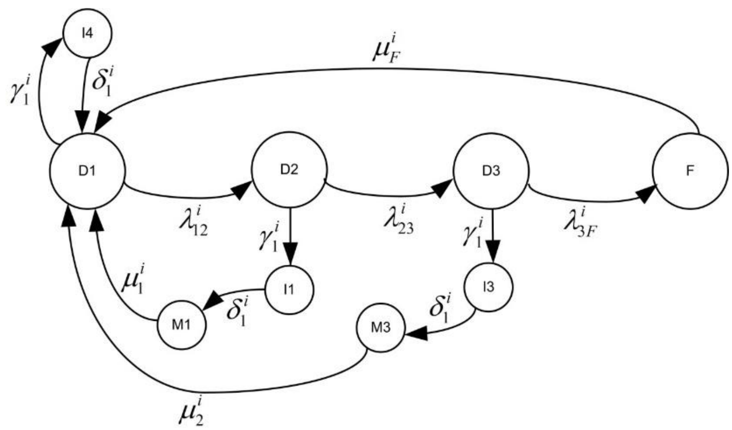

Fig. 5. Markov model with major maintenance of D_3 and minor maintenance of D_2

In this case, it is not possible to use the combination model, because the D_{22} does not have any inputs, so it will be removed from the Markov model. In fact, because of major repair of D_3, the failure mode is transmitted directly to D_1 mode, and there is no information about the time when failure mode is in D_2 mode.

3. Time based maintenance using Markov model

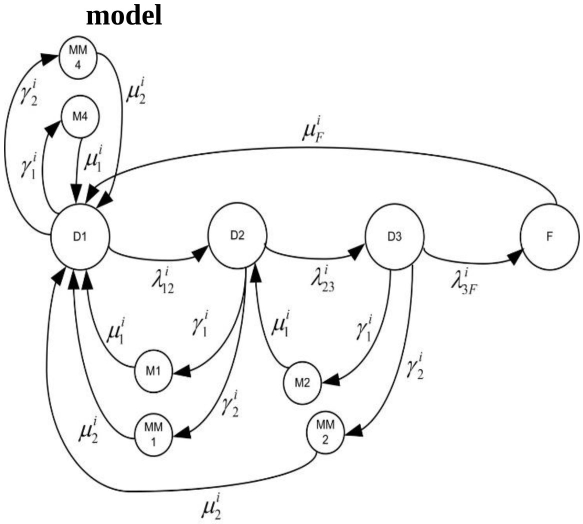

Fig. 6. Time based maintenance using Markov model

In TBM, maintenance is independent from the mode state, so it's not necessary to use the combined Markov model for modeling non-periodic maintenance. According to explanations, Markov's model can be seen in Fig. 6. As shown in Fig. 6, minor repairs are carried out at the rate of γ_1^i, and major repairs are carried out at the rate of γ_2^i. Since repairs are done blindly, these rates must be entered in the all states. This could be a disadvantage for the TBM, because repairs in D_1 mode are pointless, and the repair output is the same as the current state. Also, the major repairs in D_2 mode will be in vain, as the major repair output will be the same as minor repair, and the system cost will be increased. This kind of repair is helpful only in D_3 mode.

Finally, the run-to-failure (RTF) Markov model also must be considered, so that different options could be compared to the non-repair. This is the classic maintenance model which is shown in Fig. 1.

Up to now, six maintenance models (CBM1, CBM2, CBM3, CBM4, TBM, RTF) have been introduced, then it is necessary to present the optimization and the equations of repairs for each of these six models. Due to the limited page-number, only the economic calculations for CBM1 model are presented.

5. Economic Calculations for CBM1 Model

In this case γ_1^i and γ_2^i will be the decision variables. In other words, the optimal inspection rates should be determined to achieve the optimization of the state, the objective function of the optimization is written in Eq. (1),

$$Min_{\gamma_1^i,\gamma_2^i} Cost = IC + MC + FC + InC1 + InC2 \qquad (1)$$

In the above equation, *IC* is the cost of inspection, and *MC* is the cost of maintenance, *FC* is the equipment failure cost for the investigated failure mode. For example, the cost of repairing an out of service oil-immersed transformer because of insulation deterioration, all the parameters should be considered. The *InC1* will be the cost of consumers' blackout, which considered equipment is in the first order cut set, and eventually the *InC2* will be the cost of consumers' blackout, which considered equipment is in the second order cut set. It is clear that the *IC* and *MC* parameters are the cost of inspection and maintenance, and the next three statements are modeling the risk cost of equipment failure. Changing inspection rates indicate an inverse effect for these two types of statements, which makes the inspection rate at the particular point.

By using the Markov model in Fig. 2, the costs equation could be shown as follows,

$$\begin{aligned}
IC^{on} &= \begin{pmatrix} (P_{D_1}^i + P_{D_{21}}^i + P_{D_{31}}^i)\gamma_1^i \\ +(P_{D_{22}}^i + P_{D_{32}}^i)\gamma_2^i \end{pmatrix} CIns^i \\
MC^{on} &= \left(P_{M_1}^i + P_{M_2}^i\right)\mu_1^i CMain^i \\
FC^{on} &= \left(P_{D_{31}}^i + P_{D_{32}}^i\right)\lambda_{3F}^i CFail^i \\
InC1^{on} &= \left(P_{M_1}^i + P_{M_2}^i + P_F^i\right) L1 \times CIntr \\
InC2^{on} &= \begin{pmatrix} (P_{M_1}^i + P_{M_2}^i)P_F^{(2)}\mu_1^i T_{MF} \\ +P_F^i P_F^{(2)}\mu_F^i T_{FF} + P_F^i P_F^{(2)}\mu_F^{(2)} T_{FF} \end{pmatrix} L2 \times CIntr
\end{aligned} \qquad (2)$$

$CIns^i$ is the cost of each inspection, $CMain^i$ is the cost of each minor maintenance and $CFail^i$ is the cost of the system for the *i*-th failure mode. *CIntr* is the cost of consumers blackout in the unit of \$/(MWh). $P_F^{(2)}$ is the probability of an equipment being out of service in the second order cut set and T_{MF} is the time that it takes one of the two equipment in the cut sets enter into the circuit (for example, this time could be the minimum time that it takes the equipment under-repair return back to the network or repair the faulty equipment). T_{FF} i is the time that it takes the maintenance team return back one of the two equipment in cut set to the network. *L1* is the value of the customer's load, which equipment is in its first order cut set and *L2* is the value of the customer's load, which equipment is in its second order cut set.

Now that the economic equation of the maintenance model has been determined, the optimization process could be determined. As mentioned earlier, the decision variables are γ_1^i and γ_2^i in this model. Planning horizon for this issue is one year and due to the implementation limitations of sending the repair and inspection team which usually they cannot check earlier than one week for particular mode. So, we should change the γ_1^i rate from 54 times a year to 1 time a year and subsequently, in each selection of γ_1^i, we change the value of γ_2^i from 54 times a year to γ_1^i. And we calculate the cost of the maintenance system for all the modes. In this process it is assumed that the γ_1^i rate is always greater than the γ_2^i rate, which is the correct assumption because if the failure mode condition deteriorates the inspection rate will increase how we expect in practice.

6. Numerical Results

In this section, the proposed algorithm for scheduling of preventive maintenance is implemented on a sample equipment with four failure modes and its results are analyzed. The values for transition rates, average of repairs time, maintenance costs, and other required information are presented in Table 1. It is also assumed that $P_F^{(2)} = 0.1$

and $(\mu_F^{(2)})^{-1} = 40\ days$. The customer's loads which the equipment is in their first-order cut set, is equivalent to 1 kilowatt and the customer's loads which their equipment is in the second-order cut set, is equivalent to 20 kilowatts. The cost of customer's blackout is 0.67 $/kW.

Based on the above information, economic calculations for each of the four failure modes were performed. For example, the optimization results of the CBM3 maintenance model for failure mode 1 were obtained as shown in Fig. 7. The results for each failure mode and each of the six optimized maintenances model are shown in Fig. 8. The best maintenance strategy is selected for each maintenance model based on the costs and is presented in Table 2. The results show that the CBM is the best maintenance algorithm for the failure mode 1, which approximately has high transition rates (in other words, the probability of failure in this mode is high), the relative of the inspection cost with respect to repair cost is approximately low. The CBM1 maintenance model at the inspection rate of γ_1 which is equivalent to 2.4 times per year, and γ_2 equivalent to 1.2 times a year at an annual cost of 1,553$ which is selected as the best maintenance model for failure mode 1. Conversely, for the failure mode 4 with low transition rates, the RTF maintenance model with an annual cost of 555$ was selected as the best maintenance model. Also, the CBM strategy is not recommended for the failure mode 3 which has the high inspection, and TBM strategy is suggested. These results reflect the fact that the proposed maintenance algorithm in this paper is able to offer the best maintenance strategies for each mode based on maintenance cost and failure transition rates.

Table 1. ***Required information for the maintenance algorithm***

	Mod1	Mod2	Mod3	Mod4
$\lambda_{12}(occ / year)$	0.6	0.7	0.4	0.1
$\lambda_{23}(occ / year)$	0.7	0.8	0.5	0.3
$\lambda_{3F}(occ / year)$	1	0.8	0.8	0.7
$\mu_1^{-1}\ (day)$	1	0.5	0.25	2
$\mu_2^{-1}\ (day)$	2	1	0.5	4
$\mu_F^{-1}\ (day)$	40	50	30	10
$T_{MF}\ (day)$	0.5	0.5	0.5	0.5
$T_{FF}\ (day)$	1	1	1	1
CIns($)	200	100	5000	400
CMain($)	1200	3000	100	2000
CMMain($)	10000	3500	1000	20000
CFail($)	12000	15000	20000	8000

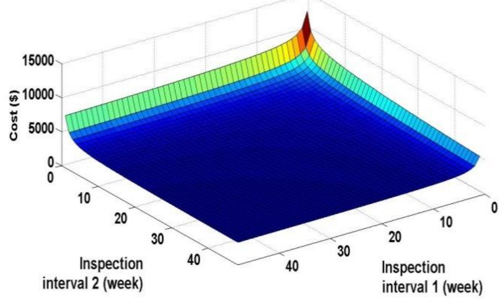

Fig. 7. The effects of γ_1 and γ_2 on performing cost of CBM3 on failure mode 1.

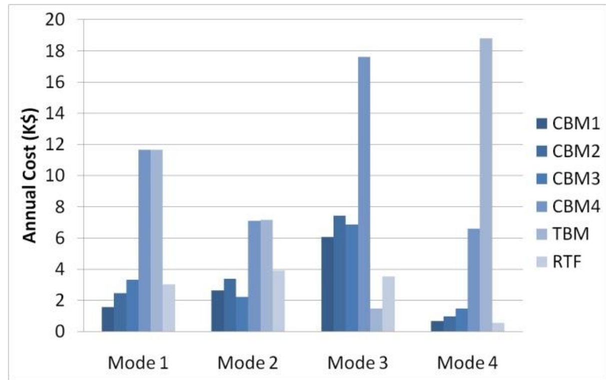

Fig. 8. The six optimized maintenances model costs for each failure mode

Table 2 The best maintenance strategy for each failure mode

	Mod1	Mod2	Mod3	Mod4
	$CBM\ 1_{2.4,12}$	$\text{CBM3}_{3,6}$	$\text{TBM}_{2,1}$	RTF
Annual Cost (k$)	1.553	2.223	1.48	0.555

7. Conclusion

In this paper, comprehensive algorithm for long term scheduling of preventive maintenance in the electric transmission networks was proposed. This algorithm has the capacity, which provides the optimal maintenance strategy for any failure mode. In this paper, by using six optimized maintenances model, the best maintenance strategy with optimized inspection, was extracted based on information about the history of the components and the components deterioration in any failure mode in the transition rates frame which introduced in this paper. The results of the algorithm implementation on a sample equipment with four failure modes expressed that, the proposed maintenance strategies based on this algorithm are in full compliance with two factors of inspection cost and repair cost, as well as the probability of failure.

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