

Integrated Preventive and Predictive Maintenance Markov Model for Circuit Breakers Equipped With Condition Monitoring

A. Karimabadi*, M. E. Hajiabadi**^(C.A.), E. Kamyab***, and A. A. Shojaei*

Abstract: The Circuit Breaker (CB) is one of the most important equipment in power systems. CB must operate reliably to protect power systems as well as to perform tasks such as load disconnection, normal interruption, and fault current interruption. Therefore, the reliable operation of CB can affect the security and stability of power network. In this paper, effects of Condition Monitoring (CM) of CB on the maintenance process and related costs are analyzed. For this, A mathematical formulation to categorize and model equipment failures based on their severity is developed. By CM, some of the high severity failures, named major failures, can be early detected and be corrected as a minor failure. This formulation quantifies the effect of CM on the outage rate and Predictive Maintenance (PDM) rate of equipment. Also, by combining the predictive maintenance to preventive maintenance, the Integrated Preventive and Predictive Maintenance Markov model is presented to analyze the effect of CM on the maintenance process. Finally, the optimal inspection rates of CBs based on the minimum maintenance cost in the traditional and the proposed Markov model are determined. To verify the effectiveness and applicability of the method, the proposed approach is applied to the CBs of KREC in Iran.

Keywords: Maintenance, Condition Monitoring, Markov Model, Optimal Inspection Rate, Circuit Breaker.

Nomenclature

A_x	Factor failure type x of equipment
n_x	Number of failure type x occurred
A_y	Factor failure type y of equipment
n_y	Number of failure type y occurred
n_s	Number of failure type x occurred with Sensor detection
A_s	Number of failure type y occurred with Sensor detection

P_S	Probability of being healthy sensors
Q_m	Probability of being faulty m sensor
Q_n	Probability of being faulty n sensor
f_i	Frequency of occurrence of each state in the maintenance model
C^I	Average cost per inspection activity
C^M	Average cost per minor maintenance activity
C^{MM}	Average cost per major maintenance activity
C^R	Average cost per equipment replacement
f_{I_i}	Frequency of occurrence of the i -th inspection state in the PM
f_{M_i}	Frequency of occurrence of the i -th minor maintenance state in the PM
f_{MM_i}	Frequency of occurrence of the i -th major maintenance state in the PM
f_F	Frequency of occurrence of equipment replacement
f'_{I_i}	Frequency of occurrence of the i -th inspection state in the proposed Markov model
f'_{M_i}	Frequency of occurrence of the i -th minor maintenance state in the proposed Markov model

Iranian Journal of Electrical and Electronic Engineering, 2020.
Paper first received 10 November 2018, revised 17 June 2019, and accepted 29 June 2019.

* The authors are with the Department of Electrical Engineering, Neyshabur Branch, Islamic Azad University, Neyshabur, Iran.

E-mails: ali.karimabadi90@gmail.com and shojaei2012@gmail.com.

** The author is with the Electrical and Computer Engineering Department, Hakim Sabzevari University, Sabzevar, Iran.

E-mail: me.hajiabadi@hsu.ac.ir.

*** The author is with the Khorasan Regional Electricity Company (KREC), Mashhad, Iran.

E-mail: ebad.kamyab@gmail.com.

Corresponding Author: M. E. Hajiabadi.

f'_{MM_i} Frequency of occurrence of the i -th major maintenance state in the proposed Markov model

1 Introduction

CM systems are widely used currently in power substations to monitor the health condition of a piece of equipment [1]. Equipping substation elements with CM has a direct impact on the reliability studies and the maintenance scheduling of the network. The scheduled maintenances are divided into three groups: Preventive Maintenance (PM), condition-based maintenance (CBM), and predictive maintenance (PDM) [2].

1.1 Preventive Maintenance (PM)

In the PM, the inspections and maintenance process is performed periodically on the equipment. PM activities are often modeled through using a classical state diagram with a periodic inspection rate [3-5]. The maintenance activities were modified in order to increase the frequency of inspection based on knowledge of the level of equipment failure so that non-periodic inspection rates could be introduced to illustrate state diagrams in maintenance modeling [6-12]. The majority of the study reported in the literature focus on designing a maintenance problem to determine the optimal maintenance rates [13-19]. Many of the probabilistic maintenance models designed for PM are based on classical state diagrams. Maintenance models provide accurate results based on classical state diagrams when the inspection rate is periodic. However, the results of classic state diagrams are not accurate under the non-periodic inspection rate. Therefore, it is necessary to propose a better model to present the actual situation and provide accurate results for using state diagrams in future maintenance modeling. In some other applications [6-8], [10], state diagrams are used to model maintenance policies with a non-periodic inspection rate, which in them, the frequency of inspection, increases with the increase of the failures. To this end, Markov's maintenance model, which is the most popular approach in maintenance modeling, was proposed to solve problems. The probabilistic Markov maintenance model is used to quantify the effect of various inspection and maintenance rates on the equipment lifetime and the associated costs [13-15] and [20, 21]. Optimal inspection and maintenance rates reduce the costs associated with the equipment replacements, while improving the equipment's lifetime [13-15]. Reference [15] applies a maintenance model, which combines both repairable and aging failure modes with maintenance activities, with a mixed set of equipment consisting of CBs and transformers. This reference optimizes the inspection rate using minimization of the total cost counting maintenance, failure, loss, repair, replacement, and patrol costs. The

organization of the maintenance process of the system components based on the reliability of the system is known as Reliability-Centered Maintenance (RCM) which is discussed comprehensively in [16, 17]. Some studies reported in the literature [18] were aimed at determining the optimal maintenance strategy for an electric power supply as a realistic complex system with a given reliability constraint.

Reference [22] utilizes the proportional hazard model to understand and quantify the impact of explanatory variables on the failure rate of circuit breakers (CB). Particularly, 4496 work orders with 2622 high voltage CBs are investigated with an occurrence of 281 major failures. Different explanatory variables such as CB type, manufacturer, preventive maintenance (PM), and others are gathered to quantify their significance and magnitude of their effect. The results present that PM has a positive impact, the number of operations within the last year a negative impact, and age has a small but negative impact on the failure rate. The CB type is not significant in all analyses which can be explained by examining the PM and age of these CB types. This paper contributes to the understanding of how explanatory variables impact the failure rate which is essential for power system asset management.

Reference [23] presents a hybrid approach for prognostics of CBs, which integrates deterministic and stochastic operation through piecewise deterministic Markov processes. The main contributions of this paper are: 1) the integration of hybrid prognostics models with dynamic reliability concepts for a more accurate RUL forecasting and 2) the uncertain failure threshold modeling to integrate and propagate uncertain failure evaluation levels in the prognostics estimation process. Results show the effect of dynamic operation conditions on prognostics predictions and confirm the potential for its use within a condition-based maintenance strategy.

1.2 Condition-Based Maintenance (CBM) and Predictive Maintenance (PDM)

In recent decades, there has been observed a rapid increase in the number of studies on condition-based maintenance, partly due to the recent development of monitoring technologies. The proper design of CBM can be effective in improving the reliability of equipment. [24, 25]. A review of CBM researches is presented in [24]. In [19], implementing different maintenance approaches on a mechanical component to compare their relative benefits, the researcher concludes that, in general, the advanced CBM and PDM policies show a comparatively better performance. However, there are a number of situations in which the PM shows a more desirable performance. In [26], it is revealed that the maintenance policies in which real-time monitoring technologies are used can improve the performance of manufacturing systems. Sadiki *et al.* [26] proposed the integration of intelligent sensor networks to monitor the

equipment in its predictive maintenance activity. Reference [27] represents two main challenges in the PM strategies. First, many actual engineering systems have complex characteristics and so the fixed inspection strategies are not suitable decisions. Second, by increasing the operation time of equipment a fixed interval inspection is not tailored in practice. Therefore, this reference proposes a mixed time/condition-based probabilistic maintenance model.

Reference [28] proposes a new approach on the identification of CB's deterioration/recovery states, i.e., the so-called life-cycle assessment, using its control circuit condition monitoring data. Reliability-oriented performance indicators, which can assess the condition of different physical parts of an HV CB in real-time, are introduced first. Then, a quantitative methodology to define the probability of the CB falling into each class of deterioration/recovery states i.e., healthy, vulnerable, troubled, and failed, is proposed.

Reference [29] proposes a transformer automated self-diagnosis system that can be installed on every power supply as a part of SCADA to extract Frequency Response Analysis (FRA) graphs from transformers and offers high repeatability which is a great benefit for FRA test. So we will have an intelligent system which is able to predict the future of the transformer using the experience of not only own self but also all the transformers in an integrated network.

Reference [30] introduces the indicators for surge arrester condition assessment based on the leakage current analysis. The maximum amplitude of fundamental harmonic of the resistive leakage current, the maximum amplitude of the third harmonic of the resistive leakage current, and the maximum amplitude of the fundamental harmonic of the capacitive leakage current were used as indicators for surge arrester condition monitoring.

Artificial neural network (ANN) methods are robust and less model-dependent for fault diagnosis when the fault signature can be directly achieved using the sampling data. In this procedure, the state of the internal process will be ignored. Therefore, generalized regression neural network (GRNN) based method is presented in [31] that uses negative sequence currents (calculated from the machine's currents) as inputs to detect and locate an inter-turn fault in the stator windings of the induction motor.

Reference [32] attempts to model the effect of condition monitoring on the reliability improvement and maintenance costs of substations. However this reference does not account for the types of failures, therefore the proposed analytical model is not realistic. Moreover, the inspection rate is considered constant and the case study is very simple.

As mentioned in the literature on CBM, The use of CM devices does not mean that the PM is not required. However, a comprehensive model to evaluate the combined preventive and predictive maintenance is not

presented in researches. Although the effect of CM on the failure rate of the equipment has been investigated, the effect of CM devices on the PDM rate of equipment has not been investigated. The main focus of this paper is to present a new integrated preventive and predictive maintenance Markov model for the CB which are equipped with CM. Equipment maintenance scheduling can be carried out periodically. By CM and early detection of minor failures, requirement based maintenance, which is referred to as PDM, can be added to the periodical maintenance schedule. CM can change the time of periodic maintenance. This paper, also, determines the optimal inspection rates of equipment in the PM and the proposed Markov models. Three steps have been taken in this paper.

First Step: The unique novel idea the first step is to provide a mathematical formulation to categorize and model the failures of equipment based on their severity. CM employs information from multiple sensors. The failure Probability of smart sensors has been taken into account. In fact, by CM, some of the severity failures, known as major failures, can be readily detected and corrected as minor failures. The proposed mathematical formulation quantifies the effect of CM on the outage rate and PDM rate of the equipment. The PDM rate is used in the second step as the smart inspection rate of the equipment.

Second Step: In the second step, at first, a new integrated preventive and predictive maintenance Markov model is proposed to analyses the effect of the CM on the maintenance process and its associated costs. The proposed Markov model is the development of the previous Markov models of PM [7]. In the proposed Markov model, the PDM rates have been added to the previous maintenance model according to the relations of the first step. Then, the optimal inspection rates in the PM and the proposed Markov models are determined by minimizing the total maintenance cost. It must be noted that one of the most novelty of this paper is to determine the effect of CM on the optimal inspections rates using the proposed Markov model.

Third Step: Finally in step three, the proposed model is applied to the 132KV CBs in the Khorasan Regional Electricity Company (KREC) in Iran.

In the next section, we describe the problem including the Markov maintenance model and the calculation of its parameters. In the third section, mathematical formulation to categorize and model the failures of equipment and the effect of the CM on the failure rate of the equipment has been investigated. Section 4 addresses the proposed Markov Model. Section 5 deals with case studies. Finally, some conclusions are drawn from the obtained results in the sixth section.

2. Statement of the Problem

2.1 Markov Maintenance Model

In PM, the equipment is inspected and maintained

periodically. The Markov model is used for the quantitative evaluation of the PM on the aging process. Fig. 1 depicts a sample state diagram for equipment, which includes the aging process [7]. The aging process is shown in Fig. 1 with the help of three S_1 , S_2 , and S_3 states. In these three conditions, despite the aging, the equipment has the correct function, if no maintenance is performed on the equipment, with the continuation of the process of aging and passing through the states of S_1 , S_2 , and S_3 , The equipment will eventually enter into a state of F, which needs to be replaced. After replacement, the new equipment will be returned to S_1 again. In Fig. 1, λ_1 , λ_2 , and λ_3 are the transition rates among different situations. I_1 , I_2 , and I_3 are the inspection states. γ_1 , γ_2 , and γ_3 are equipment inspection rates. In each inspection state based on the physical conditions of the equipment, It is decided what type of repair is to be done. The M and MM states stand for the minor and major PM. After minor and major PM are performed, considering the possibilities shown in Fig. 1, the equipment status may be better, remain in the same state of the past, or even worsen due to human error [7].

In the model of Fig. 1 for the aging condition S_2 , two states $S_{2,1}$ and $S_{2,2}$ are considered. In $S_{2,1}$, the equipment is entered into the aging state S_2 . But since the operator does not notice this change, the inspection is still done at γ_1 rate. In this case, after the first inspection or maintenance, the aging condition of the equipment will be determined. For this reason, after the I_2 , M_2 , and MM_2 states, there is a possibility to move to the $S_{2,2}$ state. In other words, in the $S_{2,2}$ state, the equipment is brought to the second aging stage, and since the operator knows these conditions, the inspection is performed with the new γ_2 rate [7].

In the PM scheduling, equipment repair is conducted based on a predetermined plan, regardless of the condition of the equipment. With CM and performing PM based on the equipment needs can reduce the cost of

repairs and increase reliability. As yet, the Markov model has not been presented to demonstrate the effect of PDM on the maintenance and repair process.

2.2 Calculating Markov Model Parameters

According to the governing equations for Markov's parameters, important indices of the Markov model are probabilistic, frequency-based, and duration-based indices. The steady-state probability vector Π is calculated by the steady-state equilibrium equation (1) and considering the sum of probabilities is equal to the unit [33].

$$\Pi Q = 0 \tag{1}$$

where Q is the transfer rate matrix:

$$Q = [q_{ij}], \quad \forall i, j \in K \tag{2}$$

The diagonal elements of the matrix Q are $q_{ii} = -\sum_{j, j \neq i} q_{ij}$. By removing the row and column of Q for each state, the Q' matrix is created. Matrix Q' is used to determine the average duration time before the system enters the state as (3) [33]:

$$MTTF = -[Q']^{-1} \tag{3}$$

The frequency occurrence of state i is:

$$T_i = 1/f_i$$

$$f_i = \Pi_i \times (\sum_j q_{ij}) \tag{4}$$

The mean time to replacement is obtained from the average time before the system enters the state F in Fig. 1:

$$MTTRL = 1/f_F \tag{5}$$

2.3 Condition Monitoring in the Substation

CM in high voltage substations plays an important role in improving utilization, real-time monitoring, preventing major failures in equipment, and thus increasing the strength of the power grid. Measurement of specific parameters and quantities of power supplies by CM allows for the prediction of possible failures in equipment [34]. Table 1 describes the sensors used to CM in substation [35-38].

3 Analytical Modeling of Equipment Failures with CM

By CM on equipment, a set of failure of the equipment is detected before they become a major failure. By detecting the failure in the minor stage and with the scheduled outage by predictive maintenance, the minor failure is corrected [34]. This will definitely reduce the major failure that would lead to outages. On

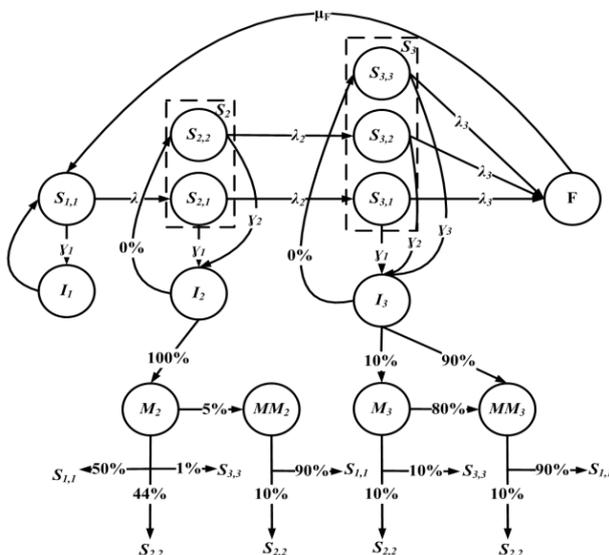


Fig. 1 State diagram of the maintenance model [7].

Table 1 Types of sensors that can be installed on Substation equipment.

Row	Types of sensors	Sensor application	Picture of sensor
1	Acoustic emission sensors	Identification oil leakage of transformer, current transformer (CT), voltage transformer (VT), tap changer, SF6 gas leakage of CBs	
2	Chemical sensors	Gas analysis of transformer, Tap changer and hydraulic oil of CBs	
3	Optical and radiation sensors	Identification arcing faults in CBs, transformer, VT, CT	
4	Acceleration, shock, and vibration sensors	Identification vibration and shock in CBs, transformer and tap changer	
5	Pressure sensors	Measuring Oil pressure of transformer, hydraulic oil pressure in CBs and gas pressure in SF6 CBs	

the other hand, it can increase the lifetime of the equipment and reduce the maintenance costs due to major failures. Therefore, for analytical modeling of the effect of CM on equipment reliability, it is necessary to model the failure factors along with their failure frequency in the equipment.

3.1 Analytical Modeling of Equipment Failures

Equation (6) shows the set of failures of equipment A, which includes X type of failure:

$$A = \{A_x\}, \quad x = 1, \dots, X \tag{6}$$

where A_x is the failure type x of equipment A. The total number of failures for N equipment of type A, in the study period of T , is in accordance with (7):

$$n_A = \{n_x\}, \quad x = 1, \dots, X \tag{7}$$

In (8), the general relation of the failure rate of equipment A is expressed based on the failure type x :

$$\lambda_x = \frac{n_x}{N T} \tag{8}$$

In this paper, failures can be divided into four categories, based on their severity:

1) The failure x does not create a problem for the system; In fact, there is a minor failure; Therefore, it can be waited for its maintenance and will be corrected in

the scheduled outage. In this case, the failure rate of equipment A, which can be corrected in scheduled outage, is defined in accordance with (9):

$$\lambda_M = \sum_{x=1}^X \lambda_x M_x \tag{9}$$

where

$$M_x = \begin{cases} 1 & \text{Failure } x \text{ will be corrected in scheduled outage} \\ 0 & \text{Other} \end{cases} \tag{10}$$

2) The failure x can be corrected in on loaded repair while there is no need to outage the equipment; In fact, there is a minor failure; In this case, the failure rate of equipment A, which is corrected in on loaded repair, is defined in accordance with (11):

$$\lambda_p = \sum_{x=1}^X \lambda_x P_x \tag{11}$$

where

$$P_x = \begin{cases} 1 & \text{Failure } x \text{ can be corrected in on loaded repair} \\ 0 & \text{Other} \end{cases} \tag{12}$$

3) The failure x is important and requires immediate sending of the repair team and emergency outage of equipment A; In fact, there is a minor failure; The failure rate of equipment A, which is corrected by the emergency outage of repair team is:

$$\lambda_e = \sum_{x=1}^X \lambda_x E_x \tag{13}$$

where

$$E_x = \begin{cases} 1 & \text{Failure } x \text{ requires an emergency outage} \\ 0 & \text{Other} \end{cases} \tag{14}$$

4) The failure x cause trip of equipment A . In fact, there is a major failure; this type of failures constructs the outage rate of equipment in (15):

$$\lambda_T = \sum_{x=1}^X \lambda_x T_x \tag{15}$$

where

$$T_x = \begin{cases} 1 & \text{Failure } x \text{ causes equipment outage} \\ 0 & \text{Other} \end{cases} \tag{16}$$

where we always have:

$$E_x + P_x + M_x + T_x = 1 \tag{17}$$

A_x in (6) is the failure type x of equipment A and occurred with the failure rate λ_x [f/yr]. This type of failure is belonged to the one category of failures based on its severity and indicated by the values M_x , P_x , E_x , and T_x . It must be noted that the equation (17) guarantees each type of failure only belong to one of the failure categories.

3.2 Analytical Modeling of CM on Equipment Failure Rate

The sensor S is supposed to be able to detect a subset of failures of equipment A in accordance with (18) and (19):

$$A_s = \{A_y\}, \quad A_s \subset A \tag{18}$$

$$n_s = \{n_y\}, \quad n_s \subset n_A \tag{19}$$

Assuming S sensors are installed on equipment A , the set of failure factors detected by smart sensors, A_{SEN} , is shown in (20):

$$A_{SEN} = \bigcup_{s=1}^N A_s, \quad A_s \subset A \quad s = 1:N \tag{20}$$

The total number of failures detected by smart sensors is defined in (21):

$$n_{SEN} = \bigcup_{s=1}^N n_s, \quad n_{SEN} \subset n_A \tag{21}$$

The CM reduces the outage rate. By installing a set of sensors, if the failure of x is of the fourth type ($T_x = 1$) which can be detected by the CM devices ($S_x = 1$), then the failure of type x will not cause equipment outage and will be deducted from the fourth type failure rate. Since the CM devices cannot detect all of the fourth-

type failures, the outage rate does not reach zero. With these definitions, (22) define the outage rate of equipment A when the CM devices detect the failures.

$$\lambda_{Tnew} = \sum_{x=1}^X \lambda_x (T_x - S_x T_x) \tag{22}$$

where

$$S_x = \begin{cases} 1 & \text{Failure } x \text{ is detected by sensors} \\ 0 & \text{Other} \end{cases} \tag{23}$$

Certainly, an early detection of failure type x through CM adds this failure in accordance with (24) to the second or third failure type, which will be corrected by the action of the repair team in predictive repair. In (24), λ_{PDM} is the PDM rate:

$$\lambda_{PDM} = \sum_{x=1}^X \lambda_x (P_x + E_x + S_x T_x) \tag{24}$$

3.3 Considering Failure Probability of the Sensor and its Impact on the Failure Rates

The outage rate in (22) can be corrected by considering the failure probability of sensors using the conditionally probability method [35]. For example, the outage rate of equipment A with CM by sensor s is:

$$\lambda_{Tnew} = (1 - \text{sensor failure probability}) \times \lambda_{Tnew} (\text{sensor is Healthy}) + (\text{sensor failure probability}) \times \lambda_T (\text{without sensor}) \tag{25}$$

If considering a set of sensors, the outage rate of equipment A with considering the sensors failure probability is:

$$\lambda_{Tnew} = \lambda_{Tnew} \left(\prod_{s=1}^N P_s \right) + \sum_{m=1}^N \left(\lambda_m \left(\prod_{N \neq m} P_s \right) Q_m \right) + \sum_n \sum_m \left(\lambda_{n,m} \left(\prod_{N \neq n,m} P_s \right) Q_n Q_m \right) + \dots \tag{26}$$

That λ_m is the outage rate A , assuming the proper function of all CM devices except CM device m . $\lambda_{n,m}$ is also the equipment outage rate, assuming the proper function of CM devices except CM devices n and m . In this study, it is assumed that the probability of simultaneous failure of the two CM devices and more is equal to zero. The PDM rate in (24) can be corrected similarly.

4 Integrated Preventive and Predictive Maintenance Markov Model

In PM, the equipment is periodically inspected and maintained. The Markov model is used for quantitative evaluation of the PM on the aging process, maintenance activities, and their associated costs. By CM of the equipment using smart sensors and early detection of failures the major failures are corrected in minor

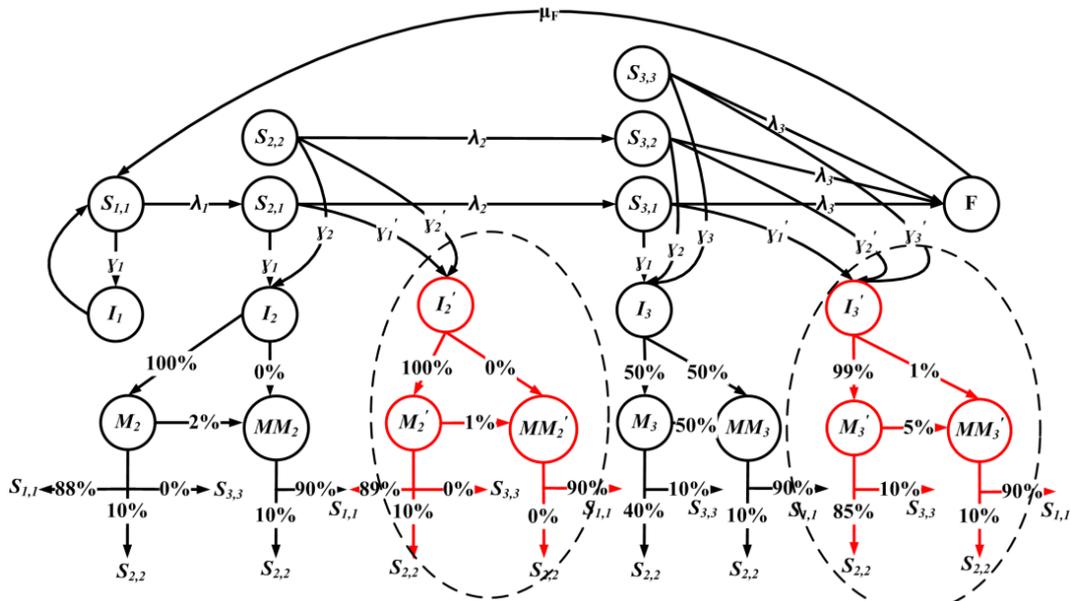


Fig. 2 A new state diagram of the Integrating preventive and predictive maintenance Markov modeling.

condition. In other words, by CM, the PDM can be added to the PM. Markov model has not been presented to demonstrate the effect of PDM, in the maintenance process, so far. Therefore, we propose a new Markov model. If, in accordance with reference [7], the aging process of equipment is considered in 3 modes, Fig. 2 shows the presented Markov model in this paper.

PM includes periodic inspections, periodic minor maintenances, and periodic major maintenances. On the other hand, PDM involves inspections based on need, minor maintenance based on the need, and major maintenance based on need. The aging process given in Fig. 2 is illustrated by the three states S_1 , S_2 , and S_3 . In these three states, despite the aging, the equipment is functioning correctly. If no maintenance is performed on the equipment, by continuing the aging process and passing S_1 , S_2 , and S_3 , the equipment will eventually enter the F -state. In F , the equipment needs to be replaced, and after replacing, the new equipment is reinstated to S_1 . In Fig. 2, λ_1 , λ_2 , and λ_3 , are the transition rates (or the rates of the aging process of equipment) between different states. I_1 , I_2 , and I_3 are inspection states in the PM mode. I'_2 and I'_3 are smart inspection status in PDM mode. γ_1 , γ_2 , and γ_3 are the equipment inspection rates for PM mode. Also, γ'_1 , γ'_2 , and γ'_3 are the smart inspection rates for equipment in PDM mode. Smart inspection rates are the same as the failure rate detected by smart sensors with the possibility of sensor failure. In each inspection state, the type of maintenance depends on the physical conditions of the equipment. The M and MM represent minor and major maintenance in the PM. The M' and MM' states, show the minor and major maintenances in the PDM, respectively. After performing minor and major PM, with regard to the possibilities shown in Fig. 2, the aging mode of equipment may be better, no change, or even worse due

to human error.

4.1 Costs of the Proposed Markov Model

The annual cost of the PM model includes the inspection cost; the minor maintenance cost, the major maintenance cost, and the cost of replacing the equipment in a steady-state (F status) which are shown in (27)-(30), respectively.

$$C^{Inspection} = C^I \sum_{i=1}^3 f_{I_i} \quad [\$/\text{years/Device}] \quad (27)$$

$$C^{Minor\ Maintenance} = C^M \sum_{i=1}^3 f_{M_i} \quad [\$/\text{years/Device}] \quad (28)$$

$$C^{Major\ Maintenance} = C^{MM} \sum_{i=1}^3 f_{MM_i} \quad [\$/\text{years/Device}] \quad (29)$$

$$C^{Replacement} = C^R f_f \quad [\$/\text{years/Device}] \quad (30)$$

C^I , C^M , C^{MM} , and C^R are the mean cost per inspection activity, minor maintenance, major maintenance, and equipment replacement, respectively. Furthermore, f_{I_i} , f_{M_i} , f_{MM_i} , and f_f are the frequency occurrence of the inspection, minor maintenance, major maintenance, and equipment replacement, respectively. The annual costs of the PDM are shown in (31)-(34) respectively.

$$C^{Inspection} = C^I \left(\sum_{i=1}^3 f_{I_i} + \sum_{i=2}^3 f_{I'_i} \right) \quad [\$/\text{years/Device}] \quad (31)$$

$$C^{Minor\ Maintenance} = C^M \left(\sum_{i=1}^3 f_{M_i} + \sum_{i=2}^3 f_{M'_i} \right) \quad [\$/\text{years/Device}] \quad (32)$$

$$C^{Major\ Maintenance} = C^{MM} \left(\sum_{i=1}^3 f_{MM_i} + \sum_{i=2}^3 f_{MM'_i} \right) \quad [\$/\text{years/Device}] \quad (33)$$

$$C^{Replacement} = C^R F_F \quad [\$/\text{years/Device}] \quad (34)$$

Equation (35) Indicates the annual maintenance costs. The frequency occurrence of the PDM states is zero, if the PM is applied.

$$C_{Total}^{Maint} = C^I (\sum_{i=1}^3 f_{I_i} + \sum_{i=2}^3 f_{I'_i}) + C^M (\sum_{i=1}^3 f_{M_i} + \sum_{i=2}^3 f_{M'_i}) + C^{MM} (\sum_{i=1}^3 f_{MM_i} + \sum_{i=2}^3 f_{MM'_i}) + C^R F_F \quad (35)$$

4.2 Determining the Optimal Inspection Rates

Most of the literatures analyze a strategy where inspections and maintenance are performed with a constant rate, which is independent of the condition of the system. This means that the inspection rates in Fig. 2 are equal having the same value [4, 5]. In some other applications [6, 10], however, state diagrams are used to model maintenance policies with non-periodic inspections where the inspection rate increases as deterioration increases. The inspection rate usually depends on the stage of deterioration of the equipment. In this paper, the optimal inspection rates are determined by minimizing the total maintenance cost in (35). For this, the inspection rates $\gamma_1, \gamma_2,$ and γ_3 are varied from minimum value, such as 0.1, to the maximum possible value. Using that, the optimal values of inspection rates $\gamma_1, \gamma_2,$ and γ_3 are determined at the minimum annual maintenance cost. It must be noted that the optimal inspection rates are determined in two situations, PM and the proposed Markov models. Therefore, proposed Markov model is implemented to determine the effect of the CM devices on the optimal

inspections rates. The cost function (35) includes the following:

- Costs of inspection, minor maintenance, and major maintenance in the PM.
- Costs of inspection, minor maintenance, and major maintenance in the PDM.
- Costs of replacing the equipment.

5 Case Studies

In this section, the failures of CBs in the Khorasan Regional Electricity Company (KREC) in Iran, and the effect of applying the CM on CBs have been studied. To do so, a statistical study was first performed on the 132kV CBs in KREC in Iran. The study was conducted during 4 years, from 2014 to 2017. The number of 132kV substations is 111, with 471 CBs. CBs failures are reported by operators and signals presented at the substation and repaired by the maintenance team. In KREC, the CBs failures are divided into four categories:

1. The failures that are corrected in scheduled outage;
2. The failures that are corrected in on load repair;
3. The failures that are corrected in emergency outage;
4. The failures that cause the trip of the equipment.

Table 2 shows the set of failure occurred in 132kV CBs in KREC during the study period. Values $M_x, P_x,$

Table 2 The set of the failures occurred in 132kV-CBs in KREC.

Failure factor	A_x	Nu [4Yr]	Rate Failure [1/Yr]	M_x	P_x	E_x	T_x	S_x
SF6 gas pressure low	A_1	31	0.016454	0	0	0	1	1
	A_2	10	0.005308	0	0	1	0	1
	A_3	5	0.002654	1	0	0	0	1
Hydraulic oil leakage	A_4	7	0.003715	0	0	0	1	1
	A_5	1	0.000531	0	0	1	0	1
	A_6	1	0.000531	1	0	0	0	1
Indicator	A_7	2	0.001062	1	0	0	0	0
Door panel	A_8	1	0.000531	0	1	0	0	0
Heater	A_9	1	0.000531	0	1	0	0	0
	A_{10}	1	0.000531	1	0	0	0	0
Numerator	A_{11}	5	0.002654	0	1	0	0	0
	A_{12}	3	0.001592	1	0	0	0	0
Disconnect or connect coil	A_{13}	2	0.001062	0	0	0	1	0
Spring charging mechanism	A_{14}	3	0.001592	0	0	0	1	0
	A_{15}	3	0.001592	0	1	0	0	0
Sf6 gas leakage	A_{16}	2	0.001062	0	0	0	1	1
Manual command	A_{17}	2	0.001062	0	1	0	0	0
Panel micro switches	A_{18}	2	0.001062	1	0	0	0	0
Contactor	A_{19}	4	0.002123	0	0	0	1	0
	A_{20}	2	0.001062	0	1	0	0	0
Loose of connections	A_{21}	1	0.000531	0	0	1	0	0
False signal	A_{22}	1	0.000531	1	0	0	0	0
Arched and defective insulators	A_{23}	2	0.001062	0	0	0	1	1
	A_{24}	17	0.009023	0	0	0	1	1
Heavy leakage of oil	A_{25}	7	0.003715	0	1	0	0	1
	A_{26}	4	0.002123	1	0	0	0	1
	A_{27}	2	0.001062	1	0	0	0	0

Table 3 The set of factors and number of the failure detected.

Equation	Set of failures factors detected by the sensors	Set of number of failures detected by the sensors
(18), (19)	$A_{s_1} = \{A_4, A_5, A_6, A_{16}\}$	$n_{s_1} = \{7, 1, 1, 2\}$
	$A_{s_2} = \{A_{23}\}$	$n_{s_2} = \{2\}$
	$A_{s_3} = \{A_1, A_2, A_3, A_{24}, A_{25}, A_{26}\}$	$n_{s_3} = \{31, 10, 5, 17, 7, 4\}$
(20), (21)	$A_{SEV} = A_{s_1} \cup A_{s_2} \cup A_{s_3} = \{A_1 : A_6, A_{16}, A_{23} : A_{26}\}$	$n_{SEV} = n_{s_1} \cup n_{s_2} \cup n_{s_3} = \{31, 10, 5, 7, 1, 1, 2, 2, 17, 7, 4\}$

Table 4 CB failure rates with the probability of failure of sensors.

CB	λ_T [1/Yr]	λ_{Tnew} [1/Yr]	λ_{PDM} [1/Yr]	λ_{Tnew^*} [1/Yr]	λ_{PDM^*} [1/Yr]
132KV	0.036093	0.004777	0.048832	0.004808	0.048801

Table 5 Transition rates of the Markov model.

Rate [1/year]	PM	Proposed model
γ_1	1.7	1.8
γ_2	8.5	12
γ_3	12	12

E_x , T_x , and S_x are in accordance with (10), (12), (14), (16), and (23). In addition, based on (8), (9), (11), (13), and (15), failures that are needed scheduled outage, failures that are corrected in the on loaded repair, failures that corrected by the emergency outage, and the outage failures are calculated.

Major failures are the results of minor failures. Therefore, the prediction of minor failures can easily avoid major failures, which ultimately results in less cost and irreversible incidents in high-voltage electricity substations [34]. One way to achieve this is CM. CM leads to early diagnosis of minor failures resulting in reduced outage failure of the CBs. Assume three sensors S_1 , S_2 , and S_3 are installed on a circuit breaker. Sensor S_1 represents the acoustic emission sensor. Sensor S_2 represents the optical sensor and sensor S_3 represents the radiation sensor. Table 3 shows the failure type and the number of failures that are detected by sensors.

λ_T in Table 4 indicates the outage rate of CB without CM and calculated by (15). The sensor failure probability is considered 0.001. λ_{Tnew} and λ_{PDM} in Table 4 show the outage rate and PDM rate of CB without considering the sensor failure probability, according to (22) and (24). λ_{Tnew^*} and λ_{PDM^*} show the outage rate and PDM rate of CB with considering sensor failure probability, according to (26). The outage rate of the circuit breaker decreases from 0.036093 f/yr to 0.004808 f/yr by CM. The PDM rate is 0.048801 f/yr. It must be noted that by considering the failure probability of sensors, the outage rate is increased and the PDM rate is decreased.

The PDM rate, λ_{PDM^*} , is used as the smart inspection rate in the proposed Markov model in Fig. 2. The proposed Markov model is used to calculate the mean time to failure (MTTF), mean time to replacement (MTTRL), inspections cost, maintenance costs, and total cost. The mean duration of inspections, minor maintenances, major maintenances, and

replacement in CBs 132KV are considered 1-hours, 1-day, 3-day and 0.1-year, respectively. The costs of inspection, minor maintenance, major maintenance, and replacement are U.S. \$250, 1000, 3500, and 40000, respectively. In addition, λ_1 , λ_2 , and λ_3 are 0.33, 0.29, and 0.5, respectively. The terms γ_1 , γ_2 , and γ_3 in Table 5 show optimal inspection rates in the PM and the proposed Markov models. The inspection rates at KREC are performed periodically and once a year. By optimizing the inspection rates to reduce the total cost of the maintenance, the periodic inspection rates are obtained 2 per year, that is, every 6 months once. In Fig. 3, Sensitivity analysis of inspection rate on the total cost of the maintenance in the PM and the proposed Markov models have been done. The periodic inspection rates in the PM and the proposed Markov models with a value of 2 and 1.9 [1/year] are optimized respectively. Figures 4-6 show the variation of the total cost of the maintenance with γ_1 , γ_2 , and γ_3 in the PM and the proposed Markov models. As can be seen in these figures, the results of the two models suggest possibilities of selecting optimal values for γ_1 , γ_2 , and γ_3 which minimize the total cost of the maintenance. The results of the PM and the proposed Markov models show that the optimal values of γ_1 , γ_2 , and γ_3 which minimize the total cost of the maintenance exist between 0.1 to 12 per year ($T^{Max} = 12$).

Table 6 compares the proposed Markov model with the PM model. Results show improvement of Markov model parameters by applying the proposed Markov model. According to the results, the inspection cost increases, while the maintenance and replacement cost decrease. The CM cost should be considered as an additional cost for the proposed Markov model. In Table 6 the installation cost of smart sensors is the difference between the total cost of the PM and the proposed Markov models. The proposed Markov model helps to calculate the lifetime of the CB by CM.

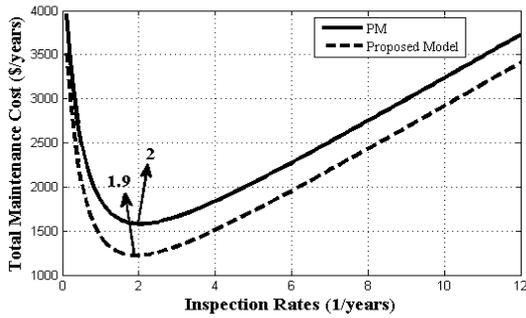


Fig. 3 Total expected cost versus inspection rate.

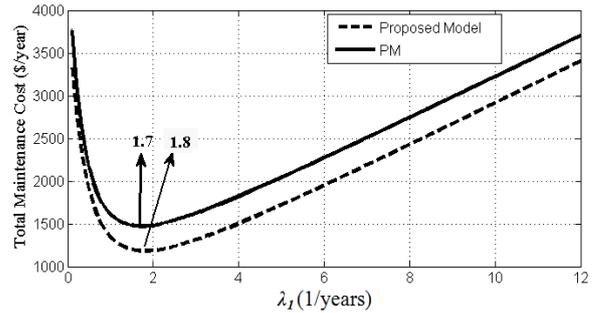


Fig. 4 Variation of the total cost of the maintenance with γ_1 .

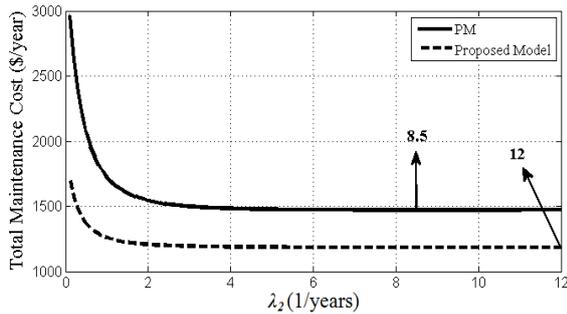


Fig. 5 Variation of the total cost of the maintenance with γ_2 .

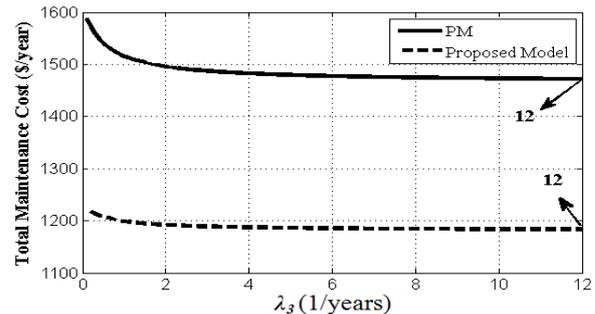


Fig. 6 Variation of the total cost of the maintenance with γ_3 .

Table 6 Probability indices and costs for maintenance models.

State	Periodic & non-optimal $\gamma_1 = \gamma_2 = \gamma_3 = 1$ [1/year]		Periodic & optimal PM: $\gamma_1 = \gamma_2 = \gamma_3 = 2$ [1/year] Proposed model: $\gamma_1 = \gamma_2 = \gamma_3 = 1.9$ [1/year]		Non-periodic & optimal	
	PM	Proposed model	PM	Proposed model	PM	Proposed model
MTTRL [years]	36.8732	49.0081	84.8301	115.1851	105.3056	122.3197
MTTF from S_1 [years]	36.7662	48.9012	84.7231	115.0782	105.1987	122.2127
MTTF from S_2 [years]	33.7356	45.8706	81.6921	112.0472	102.1678	119.1818
MTTF from S_3 [years]	24.8857	32.5678	67.7879	90.2871	81.70193	96.41642
Inspection cost [\$ /years]	233.1865	252.2502	498.4654	475.8864	462.3336	459.1905
Maintenance cost [\$ /years]	523.7372	365.4864	609.6895	397.1379	629.6931	397.3237
Replacement cost [\$ /years]	1084.799	816.1905	471.531	347.2672	379.8467	327.012
Total cost of maintenance [\$ /years]	1841.723	1433.9271	1579.6859	1220.292	1471.873	1183.526
Sensor cost [\$ /years]	0	407.7959	0	359.3939	0	288.347

Table 7 The probability of being in each state.

Number	State	Probability in PM	Probability in proposed model	Number	State	Probability in PM	Probability in proposed model
1	$S_{1,1}$	0.82062	0.847669	11	$S_{3,1}$	0.017938	0.016148
2	I_1	0.000159	0.000174	12	I_3	4.65E-06	3.60E-06
3	$S_{2,1}$	0.136083	0.130789	13	M_3	1.12E-05	4.31E-05
4	I_2	4.72E-05	3.11E-05	14	MM_3	0.000328	0.000194
5	M_2	0.001133	0.000746	15	$S_{3,2}$	0.000691	7.07E-05
6	MM_2	0.00017	4.47E-05	16	$S_{3,3}$	0.000363	0.000132
7	$S_{2,2}$	0.021437	0.003059	17	I_3	0	9.11E-08
8	I_2	0	7.46E-07	18	M_3	0	2.16E-06
9	M_2	0	1.79E-05	19	MM_3	0	3.90E-07
10	MM_2	0	5.97E-07	20	F	0.001015	0.000874

The lifetime of the CB increases by the proposed Markov model. Table 6 shows the lifetime of the CB in the periodic inspection rates and non-optimal increased by 12.1350 years and in the periodic inspection rates and optimal increased by 30.355 years and in the non-periodic inspection rates and optimal increased by 17.0141 years.

In Table 7 the probability of being at replacement

state F in the non-periodical inspection rates and optimal has been calculated. The probability of being at replacement state F decreases in the proposed Markov model, as indicated in Table 7. On the other hand, the probabilities of states S_1 , S_2 , and S_3 increase in the proposed Markov model. In fact, by CM, the aging process of equipment is delayed and the equipment needs to replace later. Bolded values in Table 7 show

Table 8 Frequency to going to major maintenances [1/year].

F_{MM} (PM)	F_{MM} (The proposed Markov model)	
$F_6=0.0206$	$F_6=0.0054$	Frequency MM_2
$F_{10}=0$	$F_{10}=0$	Frequency MM_2
$F_{14}=0.0399$	$F_{14}=0.0236$	Frequency MM_3
$F_{19}=0$	$F_{19}=0$	Frequency MM_3

that the probabilities of being in major maintenance states In the proposed Markov Model decrease significantly compared to the PM. Moreover, the frequencies of going to major maintenances in the proposed Markov model have a significant reduction compared to the PM, in Table 8.

6 Conclusion

By CM and early detection of minor failures, the PDM can be added to the PM schedule. Therefore, the integrated preventive and predictive maintenance scheduling was presented and modeled in three steps in this paper. The equipment failures were classified and modeled into 4 types of failures in the first step. This formulation investigated the effect of CM on the outage rate and PDM rate of the equipment. In the presented formulation, the failure probability of sensors was also modeled. The second step involves the usage of the proposed Markov model. Then, the optimal inspection rates in the PM and the proposed Markov models are determined by minimizing the total maintenance cost. In the third step, the failures of CBs in the KREC in Iran and the effect of applying smart sensors on them have been studied. The obtained results verify that the proposed Markov model not only decreases the outage rate of the CBs decreased, but also significantly increases the lifetime of CBs.

References

- [1] M. Compare, L. Bellani, and E. Zio, "Optimal allocation of prognostics and health management capabilities to improve the reliability of a power transmission network," *Reliability Engineering & System Safety*, Vol. 184, pp. 164–180, Apr. 2019.
- [2] E. Zio and M. Compare. "Evaluating maintenance policies by quantitative modeling and analysis," *Reliability Engineering & System Safety*, Vol. 109, pp. 53–65, 2013.
- [3] J. Endrenyi, *Reliability modeling in electric power systems*. New York: Wiley, 1978.
- [4] G. J. Anders, J. Endrenyi, G. L. Ford, and G. C. Stone, "A probabilistic model for evaluating the remaining life of electrical insulation in rotating machines," *IEEE Transactions on Energy Conversion*, Vol. 5, No. 4, pp. 761–767, Dec. 1990.
- [5] G. J. Anders, J. Endrenyi, G. L. Ford, J. Lyles, H. Sedding, J. Maksymiuk, J. Stein, and D. Loberg, "Maintenance planning based on probabilistic modeling of aging in rotating machines," in *International Conference on Large High Voltage Electric Systems*, pp. 11–309, 1992.
- [6] J. Endrenyi, G. Anders, and A. M. Leite da Silva, "Probabilistic evaluation of the effect of maintenance on reliability—An application," *IEEE Transactions on Power Systems*, Vol. 13, No. 2, pp. 576–582, May 1998.
- [7] S. K. Abeygunawardane and P. Jirutitjaroen, "New state diagrams for probabilistic maintenance models," *IEEE Transactions on Power Systems*, Vol. 26, No. 4, pp. 2207–2213, Nov 2011.
- [8] G. J. Anders and J. Endrenyi, "Using life curves in the management of equipment maintenance," in *7th International Conferenced Probabilistic Methods Applied to Power Systems*, Naples, Italy, 2002.
- [9] P. Jirutitjaroen and C. Singh, "Oil-immersed transformer inspection and maintenance: Probabilistic models," in *35th North American Power Symposium Conference*, pp. 204–208, 2003.
- [10] P. Jirutitjaroen and C. Singh, "The effect of transformer maintenance parameters on reliability and cost: A probabilistic model," *Electric power systems Research*, Vol. 72, No. 3, pp. 213–224, Dec. 2004.
- [11] S. Natti, P. Jirutitjaroen, M. Kezunovic, and C. Singh, "Circuit breaker and transformer inspection and maintenance: Probabilistic models," in *International Conference on Probabilistic Methods Applied to Power Systems*, pp. 1003–1008, 2004.
- [12] S. Natti, M. Kezunovic, and C. Singh. "Sensitivity analysis on the probabilistic maintenance model of circuit breaker," in *9th International Conference on Probabilistic Methods Applied to Power Systems*, Stockholm, Sweden, pp. 1–7, 2006.
- [13] S. K. Abeygunawardane and P. Jirutitjaroen, "Application of probabilistic maintenance models for selecting optimal inspection rates considering reliability and cost tradeoff," *IEEE Transactions on Power Delivery*, Vol. 29, No.1, pp. 178–186, Feb. 2014.
- [14] S. K. Abeygunawardane and P. A. Jirutitjaroen, "Realistic maintenance model based on a new state diagram," In *11th International Conference on Probabilistic Methods Applied to Power Systems*, pp. 299–303, 2010.

- [15] J. Zhong, Li. Wenyuan, C. Wang, J. Yu, and R. Xu, "Determining optimal inspection intervals in maintenance considering equipment aging failures," *IEEE Transactions on Power Systems*; Vol. 32, No. 2. pp. 1474–1482, Mar. 2017.
- [16] P. Dehghanian, M. Fotuhi-Firuzabad, F. Aminifar, and R. Billinton, "A comprehensive scheme for reliability centered maintenance in power distribution systems—Part I: Methodology," *IEEE Transactions on Power Delivery*, Vol. 28, No. 2, pp. 761–770, Apr. 2013.
- [17] P. Dehghanian, M. Fotuhi-Firuzabad, F. Aminifar, and R. Billinton, "A comprehensive scheme for reliability-centered maintenance in power distribution systems—Part II: Numerical analysis," *IEEE Transactions on Power Delivery*, Vol. 28, No.2, pp. 771–778, Apr. 2013.
- [18] R. Bris, P. Byczanski, R. Gono, and S. Rusek, "Discrete maintenance optimization of complex multi-component systems," *Reliability Engineering & System Safety*, Vol. 168, pp. 80–89. Dec. 2017.
- [19] E. Zio and M. Compare, "Evaluating maintenance policies by quantitative modeling and analysis," *Reliability Engineering & System Safety*, Vol. 109, pp. 53–65. Jan. 2013.
- [20] F. Yang, C. M. Kwan, and C. S. Chang, "Multiobjective evolutionary optimization of substation maintenance using decision-varying Markov model," *IEEE Transactions on Power Systems*, Vol. 23, No. 3, pp. 1328–1335, Aug. 2008.
- [21] F. Yang and C. S. Chang, "Multiobjective evolutionary optimization of maintenance schedules and extents for composite power systems," *IEEE Transactions on Power Systems*, Vol. 24, No. 4, pp. 1694–1702, Nov. 2009.
- [22] J. H. Jürgensen, L. Nordström, P. Hilber, E. Andreasson, and A. L. Brodersson, "Assessment of explanatory variables on the failure rate of circuit breakers using the proportional hazard model," in *IEEE Power Systems Computation Conference (PSCC)*, pp. 1–7, 2018.
- [23] J. I. Aizpurua, V. M. Catterson, I. F. Abdulhadi, and M. S. Garcia, "A model-based hybrid approach for circuit breaker prognostics encompassing dynamic reliability and uncertainty," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 48, No. 9, pp. 1637–1648, 2018.
- [24] S. Alaswad and Y. Xiang, "A review on condition-based maintenance optimization models for stochastically deteriorating system," *Reliability Engineering & System Safety*, Vol. 157, pp. 54–63. Jan. 2017.
- [25] P. Lin, J. Gu, and M. Yang. "An intelligent maintenance model to assess the condition-based maintenance of circuit breakers," *International Transactions on Electrical Energy Systems*, Vol. 25, pp. 2376–2393, Jul. 2014.
- [26] S. Sadiki, M. Faccio, M. Ramadany, D. Amgouz, and S. Boutahar. "Impact of intelligent wireless sensor network on Predictive maintenance cost," in *4th International Conference on Optimization and Applications (ICOA)*, Mohammedia, Morocco, pp. 1–6 2018.
- [27] H. C. Yan, J. H. Zhou, and C. K. Pang. "Machinery degradation inspection and maintenance using a cost-optimal non-fixed periodic strategy," *IEEE Transactions on Instrumentation and Measurement*, Vol. 65, No. 9, pp. 2067–2077, Sep. 2016.
- [28] P. Dehghanian, Q. Yufan, and K. Mladen "Real-time life-cycle assessment of high voltage circuit breakers for maintenance using online condition monitoring data," *IEEE Transactions on Industry Applications*, Vol. 55, No. 2, Mar.-Apr. 2019.
- [29] F. Moniri, "Modeling the frequency response movements in power transformers for predicting purposes," *Iranian Journal of Electrical and Electronic Engineering*, Vol. 2, No.1, pp. 26–33, 2006.
- [30] M. Khodsuz and M. Mirzaie, "Condition assessment of metal oxide surge arrester based on multi-layer SVM classifier," *Iranian Journal of Electrical and Electronic Engineering*, Vol. 11, No. 4, pp.354–362, 2015.
- [31] H. Yaghoobi "Stator turn-to-turn fault detection of induction motor by non-invasive method using generalized regression neural network," *Iranian Journal of Electrical and Electronic Engineering*, Vol. 13, No. 1, pp. 77–88, 2017.
- [32] Z. Kiani and M. E. Hajiabadi, "Technical and economic analysis of the effect of the smart sensor installation on the predictive maintenance and reliability improvement of substation," *The Electricity Age*, Vol. 2, No. 7, pp. 5–15. Sep. 2017.
- [33] G. Bolch, S. Greiner, H. de Meer, and K. Trivedi, *Queueing networks and markov chains: modeling and performance evaluation with computer science applications*. John Wiley & Sons, Inc. 1998.
- [34] B. Falahati, Y. Fu, M. J. Mousavi. "Reliability modeling and evaluation of power systems with smart monitoring," *IEEE Transactions on Smart Grid*, Vol. 4, No. 2, pp. 1087–1095, Jun. 2013.
- [35] J. S. Wilson, *Sensor technology handbook*, Elsevier, 2004.

[36]X. Li, "A brief review: acoustic emission method for tool wear monitoring during turning," *International Journal of Machine Tools and Manufacture*, Vol. 42, No. 2, pp. 157–165. Jan. 2002.

[37]J. G. Webster and H. Eren, *Measurement, instrumentation, and sensors handbook*, CRC Press, 1998.

[38]R. Billinton and R. N Allan, *Reliability evaluation of engineering systems*. Plenum Press, 1992.



A. Karimabadi was born in Sabzevar, Iran, He received his B.Sc. degree in Electrical Engineering from Islamic Azad University, Bojnord Branch, Bojnord, Iran, in 2012, the M.Sc. degree in Electrical Engineering from Islamic Azad University, Neyshabour Branch, Neyshabour, Iran, in 2014. Currently, he is pursuing the Ph.D. degree in Electrical

Engineering at Islamic Azad University, Neyshabour Branch, Neyshabour, Iran. His current research interests include reliability, protection, soft computing, and intelligent systems.



M. E. Hajiabadi was born in Neyshabur, Iran, in 1983. He received the B.Sc. degree from University of Sistan & Baluchestan, Zahedan, Iran, in 2005, M.Sc. degree from Sharif University of Technology, Tehran, Iran, in 2008, and the Ph.D. degree from the Ferdowsi University of Mashhad, Mashhad, Iran, in 2013, in electrical engineering. He is as

Assistant Professor of Electrical Engineering at Hakim Sabzevari University, Sabzevar, Iran. His areas of interest include power system economics and power system reliability evaluation.



E. Kamyab was born in Larestan, Iran. He received the B.Sc. and M.Sc. (Hons.) degrees from Ferdowsi University of Mashhad, Mashhad, Iran, where he also received the Ph.D. degree. He has served as a high-voltage electrical engineer at the Khorasan Regional Electric Co., Mashhad, since 1992. His research interests include distributed generation, power system protection, and transformers.



A. A. Shojaei received the B.Sc. degree from Islamic Azad University of Bojnourd, Bojnourd, Iran, in 2007. Then he pursued and received the M.Eng and Ph.D. degrees in electrical engineering both from Universiti Teknologi Malaysia in 2009 and 2014, respectively. Since 2010, he has been a Researcher in the Centre for Artificial Intelligence and Robotics, University Technology of Malaysia. Currently, he is an Assistant Professor at Islamic Azad University, Neyshabur branch. His research areas include artificial intelligence applications on power system stability and power electronics converters as well as designing neural network for power converter control in islanded and grid-connected modes.



© 2020 by the authors. Licensee IUST, Tehran, Iran. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) license (<https://creativecommons.org/licenses/by-nc/4.0/>).