Electric Power Systems Research 216 (2023) 109003

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A Petri net model for optimization of inspection and preventive maintenance rates

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ARTICLE INFO

Keywords:
Circuit breaker
Inspection
Maintenance cost
Maintenance model
Petri net
Preventive maintenance

ABSTRACT

Degradation of power system components can be reduced through preventative maintenance. In addition, optimizing inspection and preventive maintenance rates is of great importance since too little or an excessive amount of maintenance can have undesirable consequences. Conventional approaches are not applicable to practical and large-scale systems due to their inherent restrictions, such as complexity and computational burden. In this paper, a Petri net (PN) maintenance model is proposed to consider degradation, inspection, and repair processes as well as random and aging-related failures. It has great flexibility since some constraints can be imposed on the maximum number of maintenance actions, or the maintenance can be inhibited at any deterioration state without the need to change the model structure. Another advantage of this model is that it can handle the dependent deterioration among components. All the mentioned aspects are illustrated by applying the model to some circuit breakers (CBs) of the Roy Billinton test system (RBTS). The simulation results reveal that the obtained inspection rates could differ from the conventional methods resulting in lower total costs. It is also demonstrated that the proposed model can be linked with maintenance decision-making and asset management tools.

1. Introduction

The power system deteriorates as usage and age increase. Maintenance refers to all activities and actions taken to keep or restore the equipment in or to the desired level of operation in which it can do its required functions. One of the most common types of maintenance is preventive maintenance, where the tasks are done at predetermined time intervals before a failure occurs. The main aim of preventive maintenance is to postpone the probability of degradation or unplanned breakdown. Moreover, the maintenance time and cost can increase as the deterioration advances. Consequently, it is necessary to perform inspections and preventive maintenance to reduce the operational cost and keep the system in the desired condition.

Insufficient inspection and maintenance can cause early failures. However, an excessive amount of them could be very expensive; thus, there should be a tradeoff. In order to determine optimal inspection and preventive maintenance rates, it is essential to quantify the link between maintenance and reliability, which was addressed in the literature using different performance measures, including availability (or unavailability) [1–4], cost of power interruption [3,5], cost of doing the inspection, maintenance, and repair [2,3,5-7], and first passage time (FPT) [2,3,6-9].

The mentioned cost and reliability performance measures are optimized in maintenance optimization. Generally, such problems have been dealt with utilizing sensitivity analyses or optimization algorithms. In sensitivity analyses, the inspection rates are varied in order to investigate the behavior of cost and reliability measures. The optimal maintenance policy was evaluated in [2] through a multi-objective optimization using a modified simulated annealing algorithm. Stochastic-based reliability modeling was employed in [4] for maximum substation availability with aging equipment. In [5], the optimal maintenance strategies were determined using a genetic algorithm (GA) considering different transmission system components. In [10], a new approach for the estimation of maintenance criticality indices was addressed, in which the optimization problem was solved by a combination of GA and quadratic programming. In [11], an approach for maintenance decision-making and optimization using artificial neural network in multi-state component systems was proposed. A maintenance optimization model for multi-component systems considering stochastic dependent risks between components was proposed in [12]

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https://doi.org/10.1016/j.epsr.2022.109003
Received 3 December 2021; Received in revised form 14 November 2022; Accepted 17 November 2022
Available online 1 December 2022

Table 1
Characteristics of some of the maintenance studies mentioned

	[10]	[33]	[11]	[12]	[13]	[14]	[32]	[15]	[16]	[24]	Present paper
Modeling the preventive maintenance	×	✓	✓	✓	✓	×	✓	✓	✓	✓	✓
Utilizing state diagrams and/or Markov equations	×	✓	✓	×	✓	✓	×	✓	×	×	×
Addressing the link between maintenance and reliability	✓	✓	✓	✓	✓	×	✓	✓	×	✓	✓
Introducing models that cause an increase in the number of states	×	×	✓	×	×	✓	×	×	×	×	×
Utilizing multi-objective optimization	✓	×	×	×	×	×	×	×	×	×	×
Modeling the dependent deterioration among components	×	×	×	×	×	×	×	✓	×	×	✓
Determining optimal inspection and preventive maintenance rates	×	×	×	✓	×	×	✓	✓	✓	✓	✓
Utilizing PNs	×	×	×	×	×	×	×	×	×	✓	✓

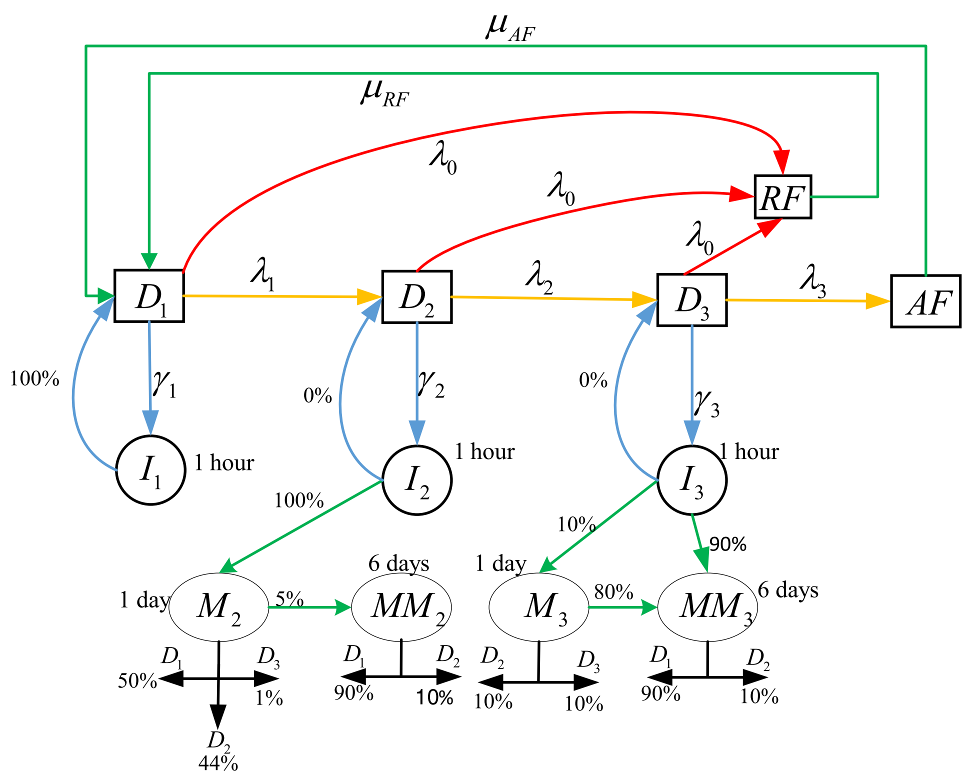


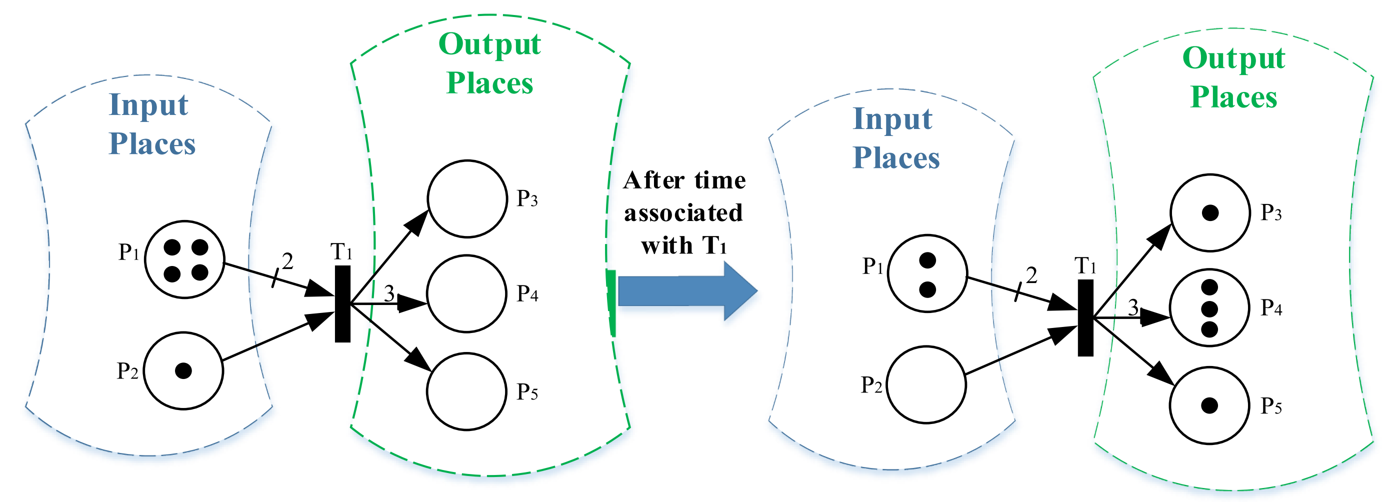
Fig. 1. Maintenance state diagram for a real CB with aging-related and random failures

using the Copula method. In [13], the optimization of the maintenance scheme for offshore wind turbines was discussed using the hybrid ant colony algorithm with discrete symbiosis organisms search algorithm.

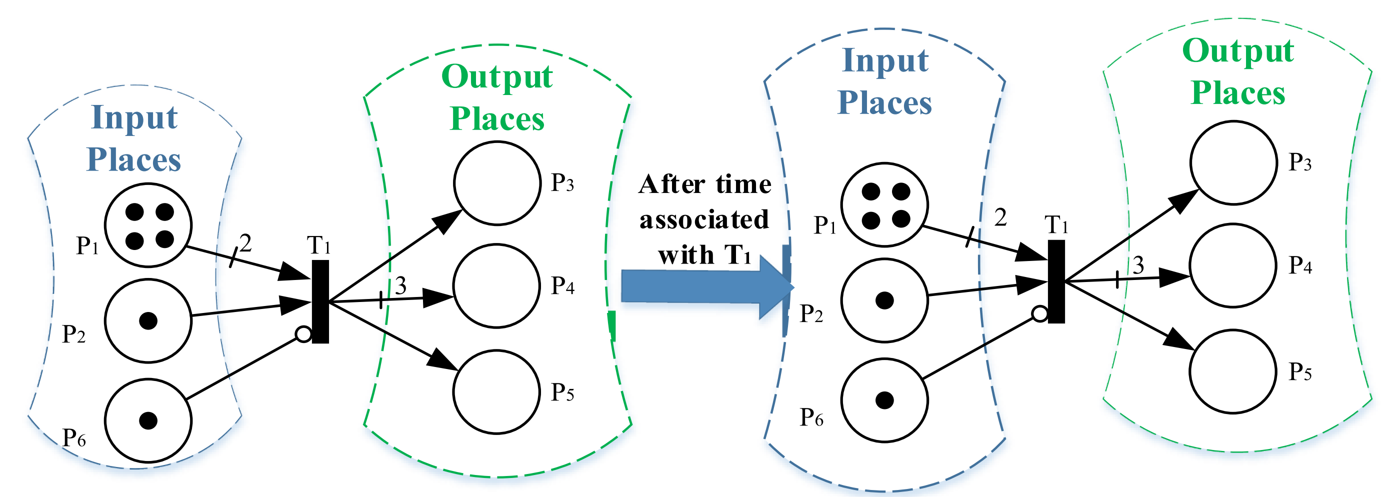
A helpful technique for maintenance modeling is state diagrams. Interest in utilizing the state diagrams has been increased due to the visualization of the sequence of events and the entire life cycle of the equipment/system, including the deterioration, inspection, maintenance, and repair. One of the common assumptions about deterioration states is that they are always known, while in practice, they should be known only after a maintenance activity or an inspection. In [8], a new state diagram was proposed to overcome the defects of classical maintenance models. In [14], maintenance policy optimization was addressed considering a partially observable system state, where the continuous-time discrete-state Markov process is utilized for the system degradation modeling. The model causes the number of states to increase, which leads to higher complexity, in particular in cases with a high number of deterioration levels.

In [15], a detailed analysis of a two-component system was carried out with the help of a condition-based maintenance (CBM) model. The effect of dependency between the degradation processes was also investigated. However, the degradation of both components was modeled as a bivariate gamma process and assumed to be revealed simultaneously, which may not be valid from a practical point of view. In [16], an approach for the CBM optimization of a deteriorating system having a large number of degradation states was presented. In [17], the stochastic dependence between system components was discussed; however, the model applications were limited due to the exponential increase in the number of system states. One of our goals in this paper is to deal with the dependency through a plain yet accurate approach.

The Petri net (PN) has been utilized as one of the most suitable modeling tools to provide a graphical representation of the system behavior since the late 1960s [18–20]. The planning of maintenance activities and operations of an offshore wind turbine was modeled in [21] employing stochastic PNs coupled with Monte Carlo simulation (MCS). The maintenance process for a wind turbine was developed in [22], and PNs were designed to simulate maintenance types and weather conditions. In [23], the development of a bridge maintenance model based on the PN method was described. An asset management framework, comprising nine PN sub-models, was proposed in [24] to predict the availability of railway network components. In [25], a PN-based model was proposed in order to estimate availability and formulate preventive maintenance planning in photovoltaic generation systems. The status of power system grid was monitored in [26] with the help of PNs in order to identify abnormal states. Although there are some maintenance studies in the literature that have already used the PN tool, such as those mentioned above, their objective is not optimal inspection



a. Example of the PN firing process



b. Example of the inhibitor arc preventing firing

Fig. 2. Examples of the firing process and the inhibitor arc. a. Example of the PN firing process. b. Example of the inhibitor arc preventing firing

rates selection.

Summarizing the approaches, they can be grouped into three general categories, namely analytical methods [2,4,6,15,27-30], simulation methods [5,7-9, 13,31,32], or a combination of both [1,3,10,33]. Analytical methods model the effect of the maintenance and the deterioration process mathematically; although their implementation is easy, some simplifying assumptions may be required, which could decrease the accuracy. Other categories, which are usually more suitable for complex problems, utilize simulation techniques, such as MCS, in their implementation. They typically need high execution time, which is their main disadvantage. Distinctive features of some of the maintenance studies discussed are presented in Table 1.

In most of the discussed studies, the inspection rates optimization problem was investigated using state diagrams and/or Markov equations. Although a state diagram is a useful tool for modeling many of the maintenance problems, its application is limited to small-scale systems due to an increase in the number of states and the state space of Markov analysis for large-scale systems, i.e., when the number of states of each component or the number of components increases [23]. In other words, they rely on the explicit description of each system state and thus, are prone to what is known as a state space explosion [34]; for example, a system of n components, each with m possible states, results in m^n states; but, by contrast, PN describes the system as a whole implicitly by utilizing a combination of the states of each component, and therefore, there is no need to depict each system state. In the literature, as mentioned above, there are some studies aiming to determine the optimal preventive maintenance rates. However, scanty research has accounted for PNs. In this paper, this research gap is filled by proposing an approach based on PN modeling, which offers a convenient analysis of the system behavior and performance evaluation even for large-scale problems [35]. The main contributions to this paper can be stated below:

- To the best of the authors' knowledge, no earlier studies using PN modeling with the aim of optimal inspection rates selection have been published to date. As discussed, unlike PN-based approaches, implementation of the conventional approaches is not feasible in large-scale problems due to their inherent restrictions, such as complexity and computational burden [8,14,17].

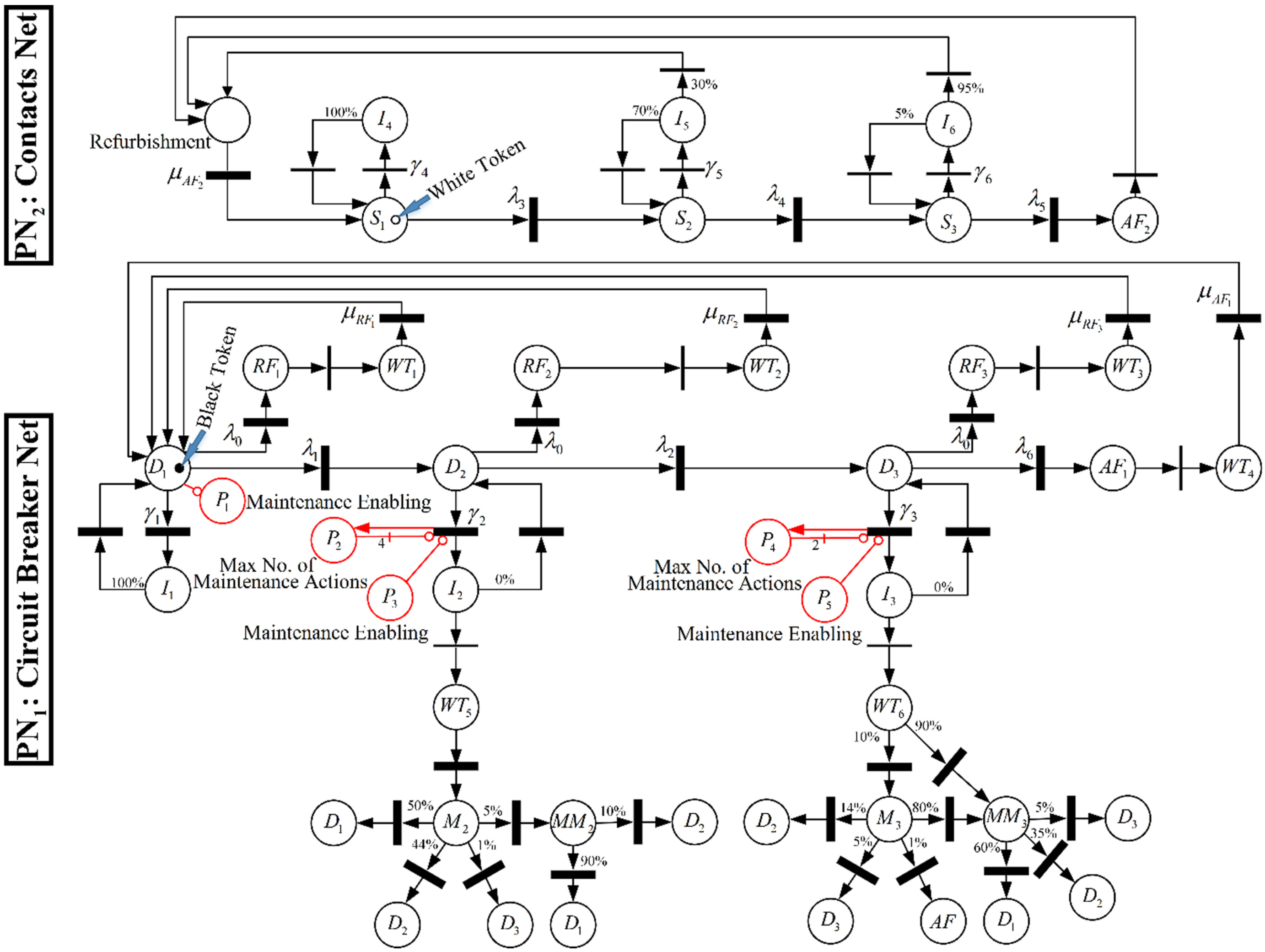


Fig. 3. Proposed PN model for the investigated CB

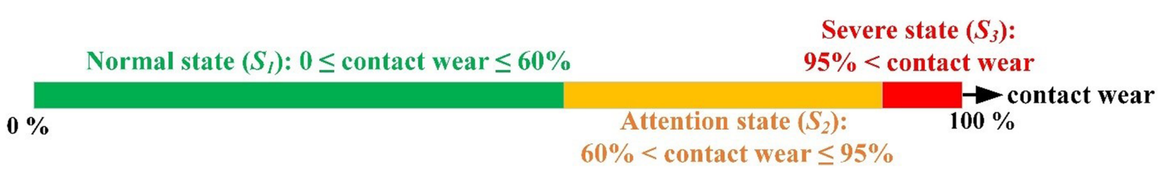


Fig. 4. Three states of deterioration for the CB contacts (S_1-S_3)

- The model has great flexibility since some constraints can be imposed on the maximum number of minor and major maintenance actions, or the maintenance can be inhibited at any deterioration state. All these capabilities and maintenance strategies can be utilized without the need to change the model structure.
- The model allows for dealing with the dependent deterioration among components.

This paper is structured as follows. The problem formulation is defined in Section 2. Section 3 describes the conventional approach with an explanation for the maintenance state diagrams. A brief definition of PN is given in Section 4. In Section 5, the proposed approach and the proposed maintenance PN model are illustrated. Next, the model efficiency is investigated in Section 6 by considering several case studies. Finally, some conclusions are drawn in the last section.

2. Problem formulation

Although the general proposed model and approach are applied to a real circuit breaker (CB), as an important switching component which was mentioned in [31], they can be extended to other power system components. In this paper, availability and cost, described and formulated in detail in [3], are the utilized performance measures. In addition, optimal values for inspection rates should be observed to find the best maintenance policy. The annual total cost (*TC*) comprises the following combination of costs [3]:

- Life cycle cost (*LCC*)
- Interruption cost *(IC)*
- Loss of profit cost (*LP*)

In order to take into account some practical restrictions such as labor, cost, and time, the sum of all inspection rates (denoted by γ) is assumed

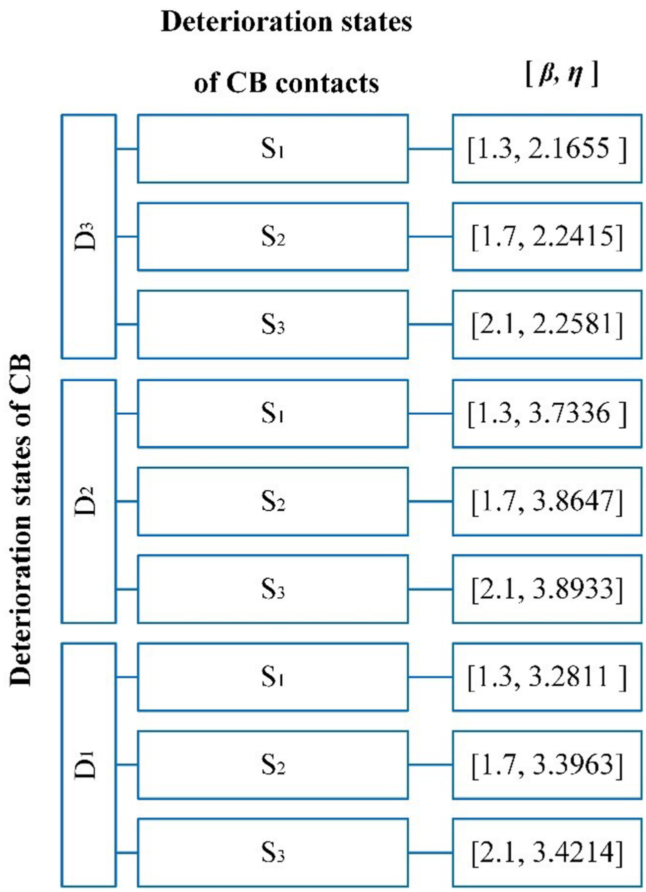


Fig 5. Weibull distributions for CB deterioration rates according to its contacts condition

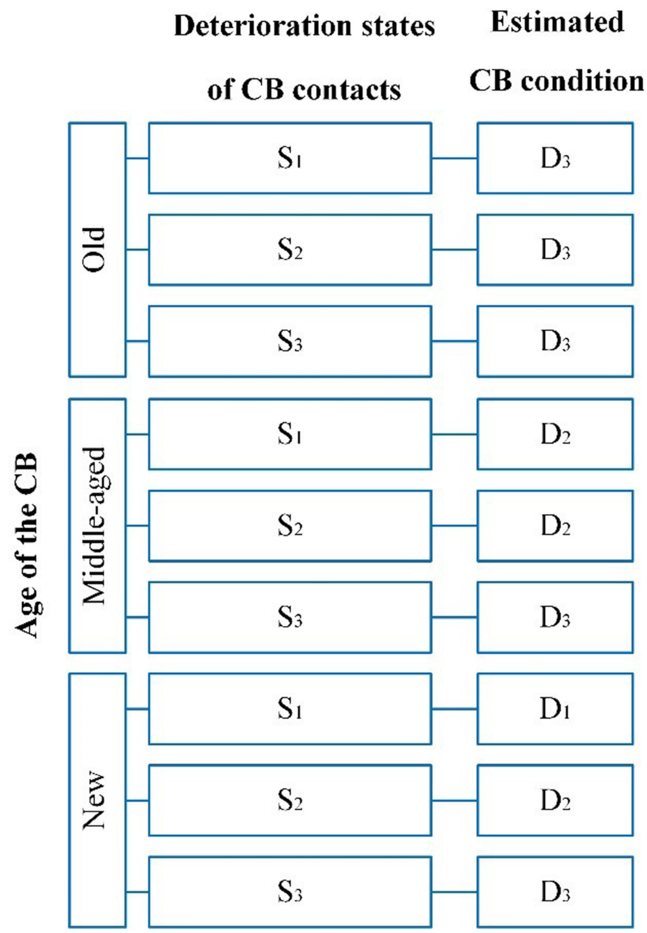


Fig 6. Estimation of current CB deterioration state

to be not higher than γ_{max}. Based on the explanations, the problem formulation can be stated as the following by assuming that the number of all CBs is N_{CB}. It should be noted that i refers to the CB_i, i.e., i-th CB.

$$\underset{\gamma_i}{Minimize} \mathrm{TC} = \sum_{i=1}^{N_{CB}} (\mathrm{LCC_i} + \mathrm{IC_i} + \mathrm{LP_i}) \tag{1}$$

$$\text{s.t.} 0 \leq \sum_{i=1}^{N_{CB}} \gamma_i \leq \gamma_{\max} i = 1, 2, ..., N_{CB} \tag{2}$$

3. Conventional approach

The state diagram and Markov equations have been usually employed in the implementation of the conventional approaches; thus, state diagrams are briefly described in this section. A classical state diagram for a real CB considering both aging-related and random failures modes and three deterioration states (D_1, D_2, and D_3) is shown in Fig. 1 [3,8,31]. D_1 and D_3 represent the best and worst degradation levels, respectively. *M, MM, I,* and *D* denote minor and major maintenance, inspection, and deterioration states, respectively. Additionally, aging-related and random failures are symbolized by *AF* and *RF*, respectively. Moreover, μ, γ, and λ represent the repair, inspection, and deterioration (or transition) rates, respectively. Despite some differences in conventional approaches, they can be broadly structured into several steps, which are presented in [36] and utilized in this study to compare the results of the previous studies with those of the proposed one.

4. PN definition

In this section, a brief and basic description of the PN concepts, required to clarify the proposed model, is provided. The graph of PN has two types of nodes: places that are denoted by circles and transitions that are denoted by thick and thin bars in the case of timed and immediate transitions, respectively. The places represent the condition of an element or the system. A token, which is denoted by a dot, is located in the place to indicate a condition presence. The transitions represent events that change the system states. Arcs that are denoted by arrows interconnect places and transitions. An input arc connects a place to a transition, while an output arc connects a transition to a place. The input or output arcs connect the input or output places to a given transition, respectively. The system state is described by marking the net, which is the distribution of tokens on the places. Arc multiplicity is the positive integer related to an arc (the multiplicity is not shown when it is equal to one). A transition is enabled if the number of tokens in all its input places equals at least the related arcs multiplicity. An enabled transition is ready for firing. In the case of transition firing, a number of tokens (that is equal to the multiplicity of the associated input arc) are removed from each of the input places, and a number of tokens (that is equal to the multiplicity of the associated output arc) are created on each of the output places. If there exists an inhibitor arc (denoted by a circle-headed arc), a transition can be enabled only when all of the inhibitor input places have fewer tokens than the associated arc multiplicity. To analyze the performance of real-world systems and processes, it is essential to introduce the duration of the events corresponding to PN transitions. However, the original PN did not convey the concept of time, and thus, transitions occurred with zero processing times, which is not the case in many practical applications. Hence, extensions of the original PN are needed. For example, in timed PNs, a specified amount of time is associated with the transitions, while in SPNs, specific probability

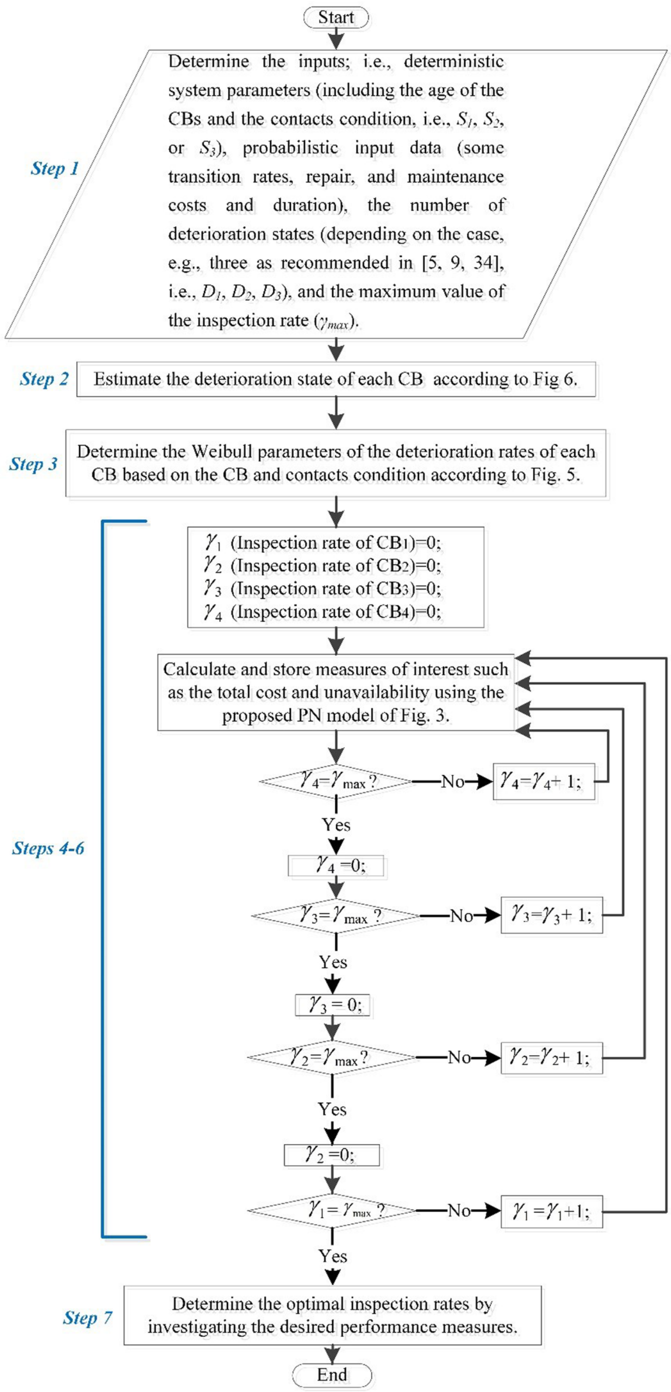


Fig. 7. Flowchart of the proposed approach

distributions are assigned to such delays. Colored PNs are another extension of PNs in which an attribute (color) is assigned to each token [37]. Examples of the firing process and the inhibitor arc are shown in Fig. 2a and Fig. 2b, respectively. In Fig. 2a, once the transition T_1 is enabled, after time delay associated with the transition, the transition fires and removes two tokens from P_1 and one token from P_2, and deposits one token in P_3, three tokens in P_4, and one token in P_5. Moreover, in Fig. 2b, the transition T_1 is not able to fire due to the existence of one token in P_6 (i.e., due to the inhibitor arc).

5. Proposed approach

Firstly, a precise knowledge of the proposed PN model is required to describe the proposed approach. Then, the optimal inspection rates selection methodology should be mentioned.

5.1. Proposed maintenance PN model

A maintenance PN model is proposed and discussed in detail in this section. Different parts of the model, shown in Fig. 3, are described as follows.

5.1.1. Degradation modeling

To investigate the CB contacts degradation and its impact on the whole CB deterioration, the proposed model is composed of two separate PNs, as shown in Fig. 3; the bottom net (PN_1) and the top net (PN_2) model the condition of the whole CB and the CB contacts, respectively. In PN_1, three deterioration states (D_1-D_3) for the CB are considered. [3]. In PN_1, the state of CB deterioration is represented by a black token. The CB contacts wear on each phase is assumed to be stored as a percentage after each operation under normal or fault conditions. Therefore, the user can monitor it, if required. It means that when the contact is new, the wear is assumed to be zero percent, and when it reaches 100%, the contact should be considered worn out. In PN_2, three states for contacts deterioration are considered, which are shown in Fig. 4 [36,38]:

It is worthwhile to note that the deterioration and transition rates, as shown in Fig 3., are denoted by λ_0-λ_6. The random and aging-related failure states will be discussed in Subsection 5.1.3.

5.1.2. Dependent deterioration modeling

The CB pole contacts undergo wear as the CB trips with or without current. The dependent deterioration is modeled by connecting the token of PN_1 (black token) to the token of PN_2 (white token). It means, firstly, the white token position determines the contacts condition. Then, the appropriate deterioration rate is selected from several defined rates based on the contacts condition. The CB degradation is modeled using a two-parameter Weibull distribution. The shape parameter, which is considered to be greater than one [7,32], increases as the contacts degrade in order to take into account the negative impact of the contacts condition worsening on the whole CB deterioration rate. Fig 5 represents the utilized shape and scale parameters of the CB deterioration rates at various contacts condition, which are denoted by β and η, respectively [36].

5.1.3. Failure modes modeling

There are generally two kinds of failure, random and aging. As the names imply, random failures occur due to random events, which may be unknown, unpredictable, and unrelated to uptime. On the other hand, the aging-related one is associated with the time in service, and as the equipment ages, it is more likely for this kind of failure to occur. Random and aging-related failures are denoted by *RF* and *AF*, respectively. It should be noted that the random failure is not considered in PN_2 for the sake of simplicity.

5.1.4. Inspection modeling

The CB should be inspected after a specified period to reveal its condition. It means after a maintenance activity or an inspection, the current deterioration state is known. However, this fact is not appropriately considered in classical state diagrams [3,8]. In this paper, to overcome this drawback, the current deterioration state of the CB before maintenance or inspection actions is estimated according to Fig 6 [36], which needs information on the CB age and contacts states. The CB is assumed to be new, middle-aged, and old in the first, second, and third 1/3 of the expected lifetime (e.g., 30 years), for the sake of brevity and simplicity. After an inspection, minor or major maintenance may be performed, or the equipment is allowed for more deterioration. If maintenance or repair is required, the process may not start immediately after the inspection; hence, defining some waiting times (denoted by WTs) in the model is needed. I_1-I_6 and γ_1- γ_6 represent the inspection

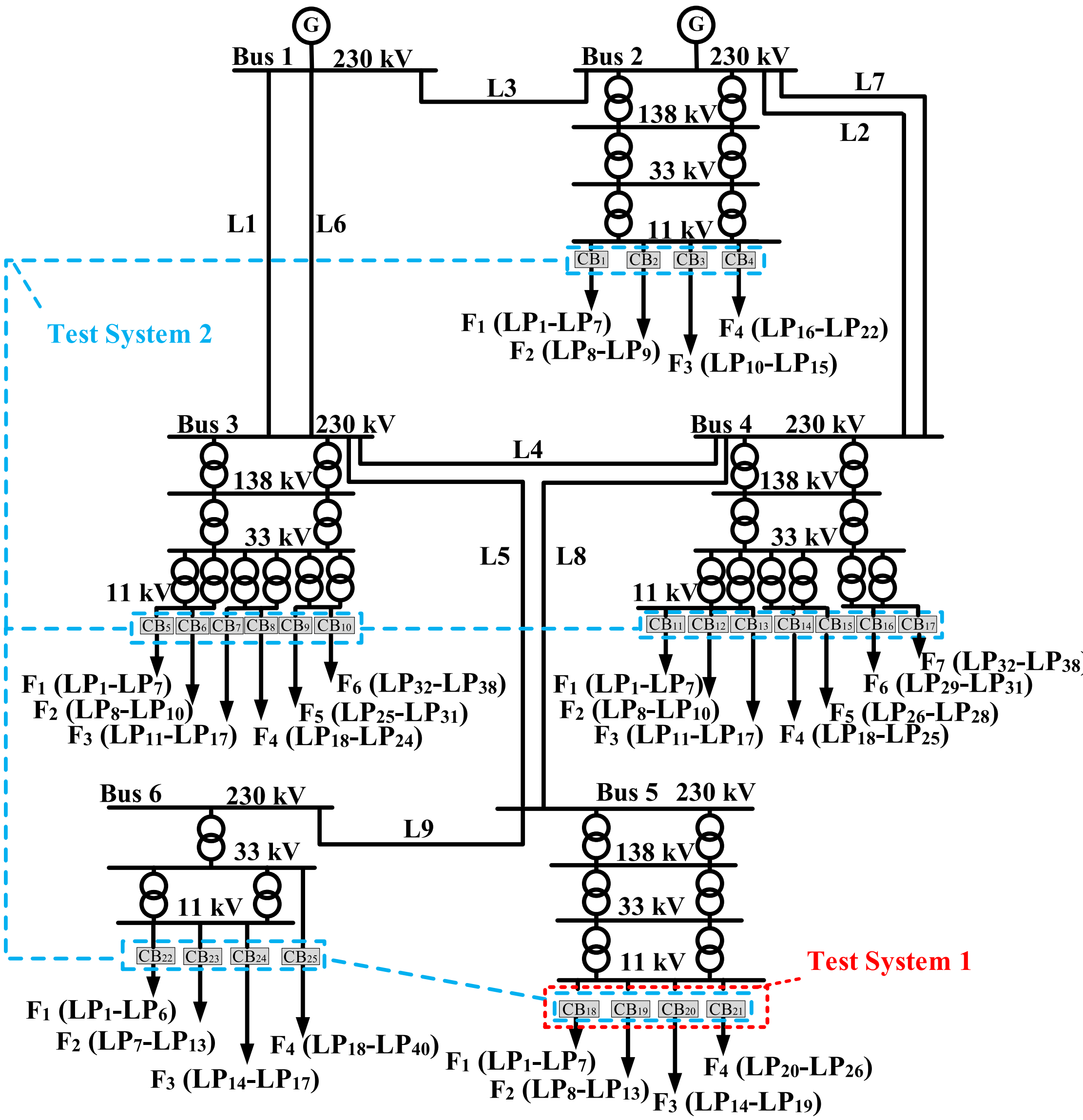


Fig. 8. Test systems

states and inspection rates, respectively. γ_4- γ_6 are associated with immediate transitions (i.e., zero time delay) due to the assumption of online and continuous contacts wear monitoring; however, γ_1- γ_3 are described with timed transitions whose values should be found optimally.

5.1.5. Maintenance and repair modeling

After performing an inspection, further information about the CB condition is provided that helps to choose the required maintenance action (major, minor, or do nothing). It is assumed that the deterioration states may degrade, improve, or remain the same by performing maintenance. This issue is implemented by assigning probabilities to the transition rates shown on the arrows in Figs. 1 and 3. Although degradation or staying the same after maintenance is not common, it is included to model maintenance error. In the model, μ_{AF} and μ_{RF} represent the aging-related and random failures repair rate, respectively. It is worth noting that the repair procedure will take longer as the equipment degrades, which could result in a lower random failure repair rate. In the proposed model, this issue is taken into account by introducing several different repair rates for random failures taking place at different degradation states. The degradation progress leads to a decrease in the repair rate, i.e., $\mu_{RF_3} < \mu_{RF_2} < \mu_{RF_1}$ [36].

5.1.6. Possible maintenance strategies modeling

In most of the previous studies, the repair and maintenance actions were performed without any limitations. However, in practice, these actions might not be effective after several times; it means the maintenance history has been almost ignored, which is not a valid assumption from a practical point of view. It should also be noted that some issues such as cost, time, and labor impose some limitations on maintenance actions [3]. These issues are overcome by introducing places P_1-P_5, shown in red in the model of Fig. 3; for example, it is assumed that the maintenance becomes ineffective after four and two times when the system state is D_2 and D_3, respectively. The places P_2 and P_4 record the number of maintenance actions, and once the predefined values (e.g., four and two) are reached, the maintenance is inhibited. Furthermore, if a token is placed in P_1, P_3, or P_5, the maintenance is totally inhibited when the system state is D_1, D_2, or D_3, respectively. Based on the mentioned explanations, four main possible maintenance strategies can be stated, which are as follows (P_1 is considered to be unmarked in all the strategies):

Table 2
Probabilistic and deterministic data

Weibull distributions		
Item	Shape parameter	Scale parameter
λ_1, λ_2, and λ_6 (per year)	Refer to Fig 5.	
Exponential distributions		
Item	Rate parameter	
λ_0 (per year)	0.11	
λ_1 (per year)	0.33	
λ_2 (per year) *	0.29	
Deterioration rate of D_3: λ_3 (per year) *	0.5	
Deterioration rate of S_1: λ_3 (per year) **	0.06	
λ_4 (per year) **	0.13	
λ_5 (per year) **	0.2	
Deterministic values		
Item	Duration	
I_1-I_3 (hour)	1	
I_4-I_6 (hour)**	0	
M_2-M_3 (day)	1	
MM_2-MM_3 (day)	6	
AF_1 (year)**	0.11	
AF_2 (year)**	0.05	
AF (year)*	0.11	
RF_1 (day)**	5	
RF_2 (day)**	9	
RF_3 (day)**	12	
RF (day)*	9	
Waiting times: WT_1-WT_6 (day)**	0	

* : Only for the conventional approach implementation
** : Only for the proposed approach implementation

Table 3
CBI values

Case study	CB no.	CBI
1	18	0.65
	19	0.35
2	18	0.6
	21	0.4
3	19	0.35
	20	0.65
4	20	0.55
	21	0.45
5	18	0.31
	19	0.22
	20	0.47
6	19	0.22
	20	0.47
	21	0.31
7	18	0.11
	19	0.11
	20	0.57
	21	0.21
8	1-25	0.04

- Strategy no. 1: Maintenance starts as soon as possible; for this aim, both P_3 and P_5 are unmarked.
- Strategy no. 2: Maintenance is inhibited when the system state is D_2; for this aim, P_3 is marked with a token, and P_5 is unmarked.
- Strategy no. 3: Maintenance is inhibited when the system state is D_3; for this aim, P_5 is marked with a token, and P_3 is unmarked.
- Strategy no. 4: Maintenance is totally inhibited, and repair is only allowed; for this aim, both P_3 and P_5 are marked with a token.

5.2. Optimal inspection rates selection

The proposed approach can be broadly outlined in the following steps for a system consisting of CB_1-CB_4. Fig. 7 shows the flowchart in detail.

Step 1: The required input data, including deterministic and probabilistic information, are collected.
Step 2: Fig. 6 is employed in order to estimate the CBs deterioration states.
Step 3: Fig. 5 is employed in order to determine the Weibull distributions of CBs deterioration rates.
Step 4: Let the desired inspection rate vary in the range [0 γ_{max}].
Step 5: The proposed PN model of Fig. 3 is employed to obtain the required performance measures.
Step 6: If all inspection rates combinations are considered, the process will continue through the next step; otherwise, it is referred to *Step 4*.
Step 7: The calculated performance measures are being investigated in order to find the optimal inspection rates.

6. Case studies and simulation results

For the purpose of illustrating the proposed and conventional approaches, two test systems according to distribution CBs of Roy Billinton test system (RBTS) are incorporated, assuming γ_{max} to be 52 times per year, unless otherwise stated [39]. The CBs failures are also assumed to be independent. As shown in Fig. 8, test systems 1 and 2 include four and 25 CBs, respectively. The CB models, described in Sections 3 and 5 and shown in Figs. 1 and 3, are utilized for the implementation of the conventional and proposed approaches, respectively. Eight case studies are defined. Case studies 1, 2, 3, 4, 5, 6, 7, and 8 include $CBs_{18,\ 19}$, $CBs_{18,\ 21}$, $CBs_{19,\ 20}$, $CBs_{20,\ 21}$, $CBs_{18\text{-}20}$, $CBs_{19\text{-}21}$, $CBs_{18\text{-}21}$, and $CBs_{1\text{-}25}$, respectively. The current states of the CB_{18} and $CBs_{1\text{-}6}$, $CBs_{19\text{-}20}$ and $CBs_{7\text{-}19}$, and CB_{21} and $CBs_{20\text{-}25}$ in case studies 1-7 and 8 are D_1, D_2, and D_3, respectively. Moreover, it is assumed that the corresponding contacts states of D_1, D_2, and D_3 are S_1, S_2, and S_3, respectively. The CBs are assumed to be unavailable only when performing maintenance and during inspections. Table 2 shows the required data, which are taken from [31,36]. Different classes of the load points of RBTS buses to which each CB is connected and the related interruption cost are provided from [36,40].

The total test system availability (A_{Total}) could be evaluated using (3), where A_{CBn} and CBI_n represent the CB_n availability and importance, respectively. More details about the *CBI*, as the weighting factor, and its calculation method can be found in [4]. The assumed *CBI* values for case studies 1-8 are mentioned in Table 3. As already mentioned, the optimal inspection rates are considered to be the ones with the minimum total cost; thus, the availability values are not of great importance and are just mentioned for the proposed approach for the sake of completeness.

$$A_{Total} = \sum A_{CB_n} \times CBI_n \tag{3}$$

A sensitivity analysis of the total cost related to case studies 1-4 toward variations of inspection rates is carried out, which is depicted in Figs. 9-10. The optimal inspection rates are shown, as well. It is assumed that there are no limitations related to the maximum number of maintenance actions to investigate the simulation results over a wide range of inspection rates. This assumption can be implemented by ignoring the places P_2 and P_4 in Fig. 3. As mentioned before, there is a total of 53 possible values for the inspection rates since they range from zero to 52. Moreover, the search spaces of case studies 1-4, 5-6, 7, and 8 are composed of 2^{53}, 3^{53}, 4^{53}, and 25^{53} values since they have 2, 3, 4, and 25 components, respectively. One possible solution for obtaining the optimal inspection rates in case studies 1-7 could be the use of a grid search algorithm (GSA) [5], i.e., the costs for a grid for all possible rates are determined and the optimal inspection rates are the ones that minimize the total cost. However, in practical and large-scale systems, there is a huge increase in the computer memory necessities and computational load due to a large number of states and components in the optimization problem. In such cases in which it is not feasible to implement methods such as GSA, a heuristic approach, such as GA [5], is

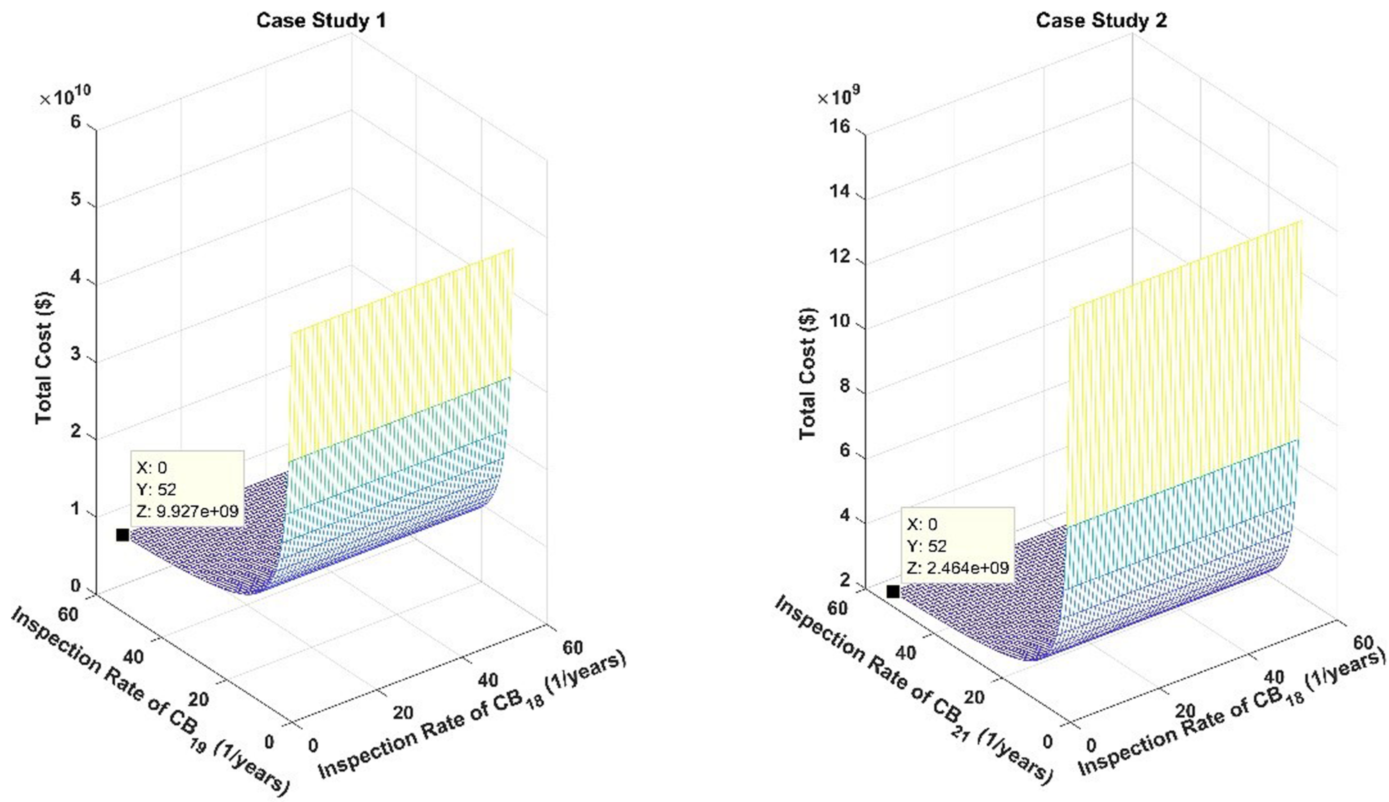


Fig. 9. Total cost versus inspection rates for case studies 1-2

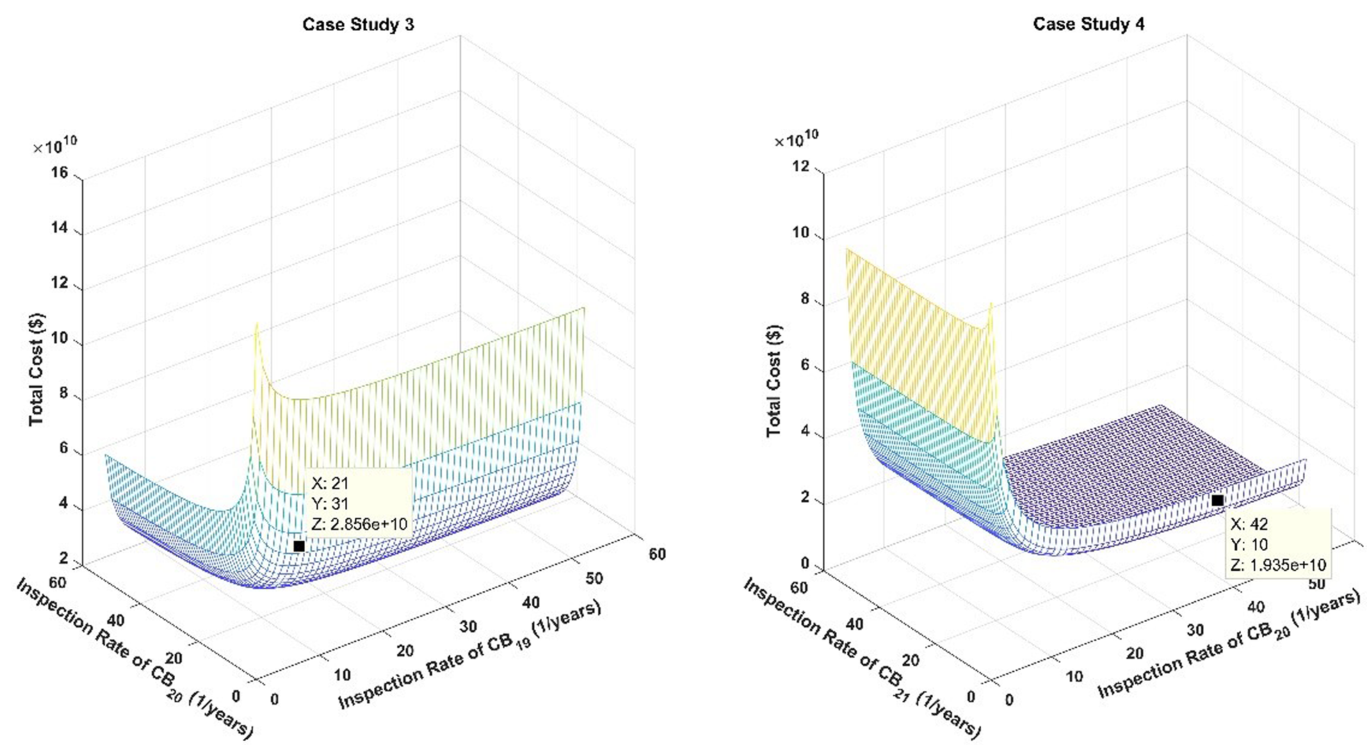


Fig. 10. Total cost versus inspection rates for case studies 3-4

Table 4
GSA and GA results for case studies 1-7

Case Study				1	2	3	4	5	6	7
Conventional Approach	Rates (per year)	GSA	CB_{18}	0	0	—	—	0	—	0
			CB_{19}	52	—	19	—	20	20	20
			CB_{20}	—	—	33	40	32	27	24
			CB_{21}	—	52	—	12	—	5	8
	Cost (10^8 \$)		CB_{18}	15.898	15.898	—	—	15.898	—	15.898
			CB_{19}	83.585	—	101.46	—	100.23	101.46	100.23
			CB_{20}	—	—	185.14	178.65	186.71	192.62	197.54
			CB_{21}	—	8.803	—	14.919	—	24.658	18.584
			Total	99.483	24.701	286.6	193.569	302.838	318.738	332.252
Proposed Approach	Rates (per year)	GSA	CB_{18}	0	0	—	—	0	—	0
			CB_{19}	52	—	21	—	21	19	19
			CB_{20}	—	—	31	42	31	26	26
			CB_{21}	—	52	—	10	—	7	7
		GA	CB_{18}	0	0	—	—	0	—	0
			CB_{19}	52	—	21	—	21	19	19
			CB_{20}	—	—	31	42	31	26	26
			CB_{21}	—	52	—	10	—	7	7
	Cost (10^8 \$)		CB_{18}	15.85	15.85	—	—	15.85	—	15.85
			CB_{19}	83.418	—	98.715	—	98.715	101.46	101.46
			CB_{20}	—	—	186.91	177.07	186.91	194.2	194.2
			CB_{21}	—	8.7857	—	16.375	—	20.027	20.027
			Total	99.268	24.6357	285.625	193.445	301.475	315.687	331.537
	Availability		CB_{18}	0.9872	0.9872	—	—	0.99648	—	0.9872
			CB_{19}	0.99693	—	0.99655	—	0.99667	0.2192256	0.99648
			CB_{20}	—	—	0.99675	0.99687	0.99637	0.4684349	0.99667
			CB_{21}	—	0.99714	—	0.99662	—	0.3088747	0.99637
			Total	0.9906055	0.991176	0.99668	0.9967575	0.9965352	0.9965352	0.9955444

Table 5
GA results of the proposed approach for case study 8

CB no.	Rates (per year)	Cost (10^8 \$)	Availability
CB1	0	21.421	0.9872
CB2	0	5.8344	0.9872
CB3	0	15.401	0.9872
CB4	0	20.729	0.9872
CB5	0	11.214	0.9872
CB6	0	19.311	0.9872
CB7	2	422.04	0.99298
CB8	1	326.93	0.99126
CB9	2	467.18	0.99298
CB10	3	173.01	0.99392
CB11	1	503.2	0.99126
CB12	2	219.43	0.99298
CB13	4	287.69	0.99453
CB14	3	355.36	0.99392
CB15	4	139.53	0.99453
CB16	4	162.78	0.99453
CB17	6	192.53	0.99524
CB18	7	202.46	0.99548
CB19	4	183.1	0.99453
CB20	2	54.137	0.99466
CB21	2	43.464	0.99466
CB22	1	14.968	0.99312
CB23	1	16.541	0.99312
CB24	2	69.972	0.99466
CB25	1	48.066	0.99312
Total		3976.298	0.9921872

one of the recommended solutions. In this paper, both GA and the GSA are applied to case studies 1-7 (Table 4), while only GA is utilized for case study 8 (Table 5). The total cost variation with the number of (cost) function evaluations (*NFEs*) is represented in Fig. 11 in order to ensure the GA convergence process. The generation number and population size for each generation related to case studies 1-7 and 8 are 200 and 150 and (both) 1000, respectively. The results of implementing GSA and GA, as represented in Table 4, are of equal values, which validates the accuracy of the GA process since GSA takes into account all possible inspection rates. Assuming the total cost of the proposed approach to be one pu, Fig. 12 depicts a comparison to the conventional one with respect to γ_{max}.

As shown by the simulation results, increase in the inspection rates of CBs in an early deterioration state, i.e., CB_{18} and $CB_{1\text{-}6}$ in test systems 1 and 2, respectively, slightly increases overall costs and degrades availability. The reason is that inspections in such states do not usually result in significant reduction of the repairs or maintenance frequency or duration, but cause the CBs to be unavailable. On the other hand, the unavailability and total cost decrease as the inspection rate increases in other deterioration states (i.e., D_2-D_3). Therefore, it is recommended to conduct inspections less and more repeatedly at primary and advanced states of deterioration. It should be noted that the exact inspection rates at all deterioration states need to be calculated. In addition, although CB_{21} and $CB_{20\text{-}25}$ are more degraded than CB_{20} and $CB_{7\text{-}19}$, i.e., state of D_3 versus D_2, in case studies 4, 6, 7, and 8, respectively, they should be generally less inspected. The reason is that such CBs have fewer total costs due to lower interruption costs or other issues. To summarize, as the degradation increases, it is recommended to perform inspections at greater rates, with the exception of case studies 4, 6, 7, and 8. The results shown in Table 4 and Fig. 12 demonstrate that the optimal inspection rates of the proposed approach in comparison to the conventional one could lead to a lower calculated total cost.

Although the proposed model can impose some inhibition on maintenance, all the results mentioned above are related to the strategy no. 1 in which maintenance starts as soon as possible, and no inhibition is considered. The results of implementing the strategies no. 2 and 3 for CB_{21} and CB_{20} are shown in Fig. 13, assuming the failure cost to be one pu. As revealed, increasing the inspection rates improves the deterioration states, decreases the unavailability and repair cost, and increases the minor or major maintenance cost. Since the repair cost is much greater than the maintenance cost, both strategies finally decrease the total cost. The average asset, i.e., the investigated CB, condition is shown as well, which refers to the probability, i.e., the proportion of the useful life, that each deterioration state has a token. As a matter of fact, it reveals the average sojourn time in each deterioration state. Since in strategies no. 2 and 3, maintenance is allowed when the system states

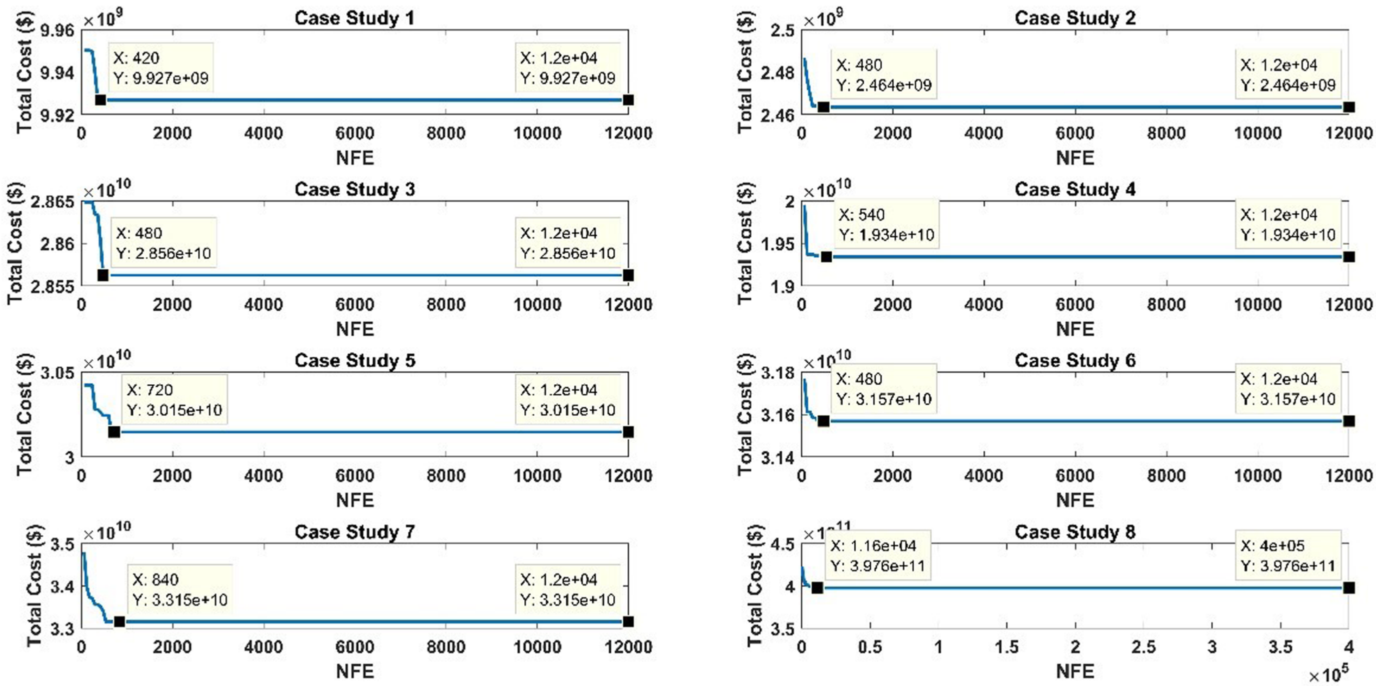


Fig. 11. GA convergence process

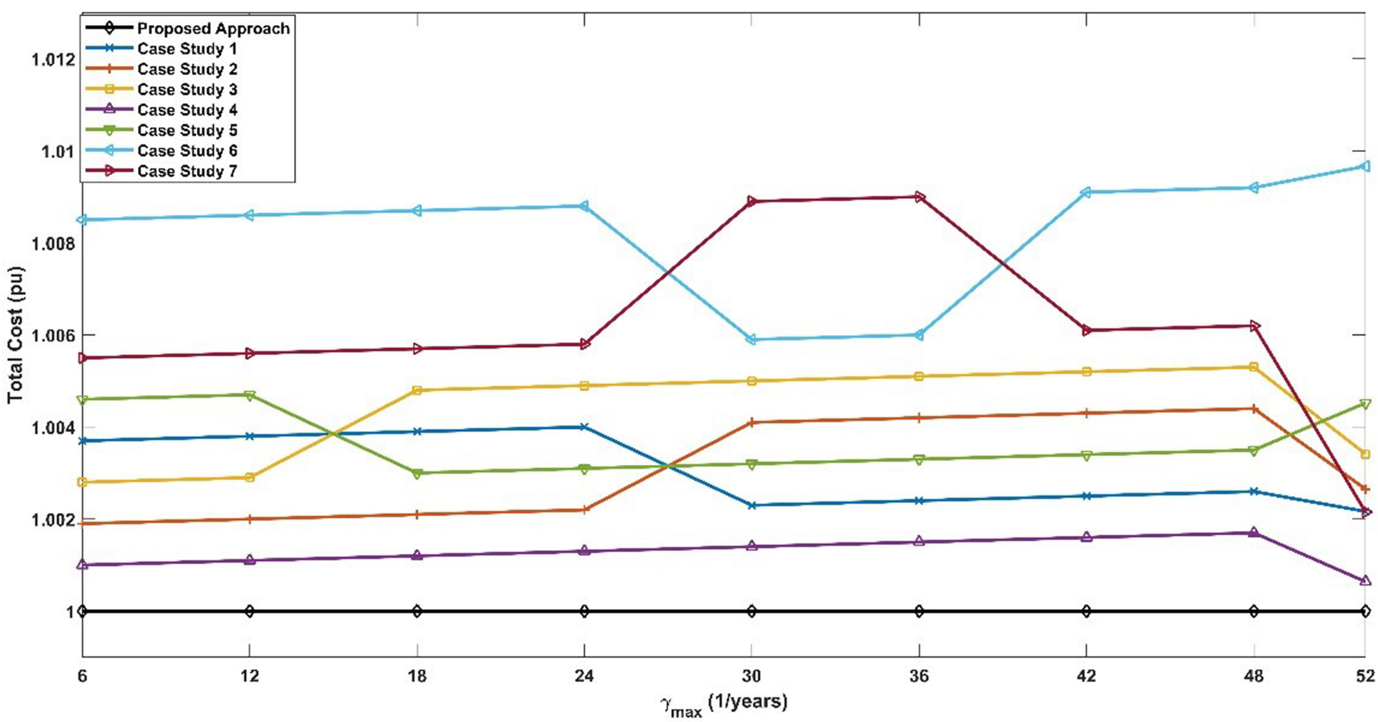


Fig. 12. Comparison between the proposed and conventional approaches with respect to the total cost (in pu) for case studies 1-7

are D_3 and D_2, respectively, the "minor deterioration (D_2)" and "as good as new (D_1)" states are improved significantly, respectively.

A CB is generally comprised of three main sections, including the operating mechanism, the control section, and the interruption chamber, which are connected in series from a reliability viewpoint [41]. Thus, the failure of each section results in CB malfunction. Moreover, CBs can be categorized according to interruption mediums as air, oil, gas, and vacuum and according to mechanism types as spring energy, hydraulic/pneumatic energy, and solenoid/magnetic [42]. Various CB types and characteristics can be taken into account by considering different model parameters, such as deterioration, failure, and repair rates as well as the duration of inspection, maintenance, and repair. In addition, there are some events, such as circuit overloads, ground fault surges, and short circuits, that can cause a CB to trip. These issues could be addressed through the proposed approach using different *LCC* and *IC* values.

It is worth noting that the findings may not be true in other real-world applications, and therefore, are restricted to the case studies

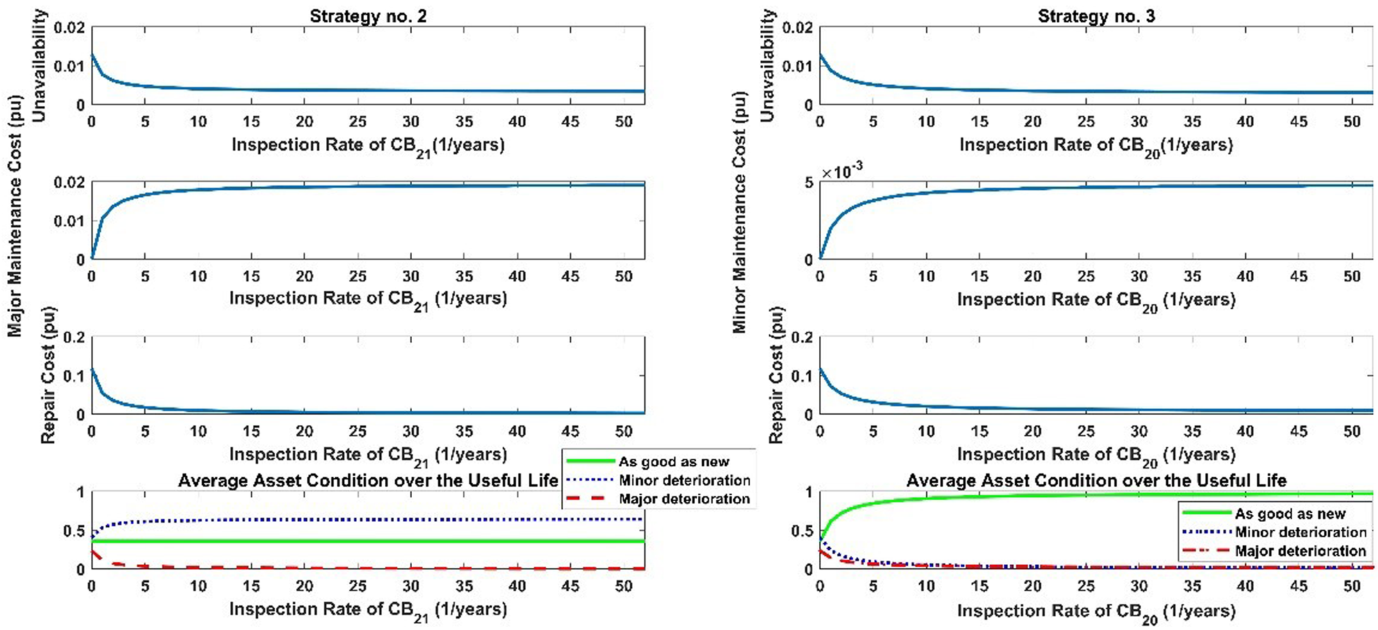


Fig. 13. Results of implementing the strategies no. 2 and 3 for CB_{21} and CB_{20}, respectively

investigated. As mentioned before, the proposed model is a general and suitable tool, which can help industries and utilities to select the best inspection rates of preventive maintenance.

7. Conclusions

This paper proposed a general probabilistic PN maintenance model. There was no need to assume constant deterioration rates. This feature enabled the model to handle the dependent deterioration process. Moreover, it could impose some restrictions on the number of maintenance actions to match practical applications more realistically in which maintenance might become ineffective after several times. The maintenance could also be inhibited at any deterioration state. It should be noted that all these capabilities could be utilized without changing the model structure. These aspects and the merits of PNs in finding the optimal inspection rates were illustrated in terms of total costs and availability by applying the model to some case studies composed of real CBs. It was shown that the optimal inspection rates of the proposed approach could lead to a lower calculated total cost compared to those of the conventional approach. It was also revealed that the proposed model could be linked with maintenance decision-making and asset management tools.

It is worthwhile to note some limitations of the proposed approach. Although in this study the model is applied to CBs, the proposed approach can be extended to other power system components such as generators and transformers. The investigation of multi-objective optimization methods could be another important research issue to deal with, as well. The present work can also be extended to address imperfect inspection.

CRediT authorship contribution statement

Farshid Nasrfard: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Mohammad Mohammadi:** Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Mazaher Karimi:** Investigation, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The authors do not have permission to share data.

Funding

This research has been supported by the University of Vaasa under Profi4/WP2 project with the financial support provided by the Academy of Finland.

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