International Journal of Industrial Engineering & Production Research December 2022 Vol. 33, No. 4: 1-19
DOI: 10.22068/ijiepr.33.4.11

RESEARCH PAPER

Clustering of Condition-Based Maintenance Activities with Imperfect Maintenance and Predication Signals

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Received 15 November 2021; Revised 10 September 2022; Accepted 3 October 2022;

ABSTRACT
Combining maintenance activities for multi-component systems is called opportunistic maintenance or maintenance clustering, which is known to be cost-effective, especially for multi-component systems with economic dependency. Every operating system is subject to gradual degradation which ultimately leads to system failure. Each level of degradation can be represented by a state. The state of a system can be estimated through condition monitoring, albeit with uncertainty. In this paper, we present a clustering model that factors in uncertainty in alerting and lifetime distribution and considers the possibility of using the imperfect maintenance approach. This model is developed for a system with three levels of warning (Signal, Alert, Alarm), which combines inspections and condition monitoring to avoid unnecessary inspections and thereby achieve better cost-efficiency. Our analysis and results provide a general view of maintenance clustering to minimize costs and maximize system availability. Different policies for clustering maintenance activities are proposed and compared. Numerical investigations performed with MATLAB software show that maintenance clustering can result in as much as 80% cost saving compared to No clustering policy. Moreover, alert clustering policy costs less than the other policies, and this cost difference becomes larger as the initial probability that the system units is weak increases.

KEYWORDS: *Condition monitoring; Imperfect maintenance; Uncertainty; Maintenance clustering.*

1. Introduction

The managers in manufacturing systems are trying to improve the efficiency of the production processes. Different factors affect the productivity and efficiency of processes. Production control and maintenance planning are the most important aspects that affect the productivity of production processes [1]. Joint planning of maintenance and production can improve the productivity of manufacturing systems and reduce the total cost of systems [2]. Research has shown that, typically, from 15 to 60% of the costs of a production unit are related to repair and maintenance activities and more than 33% of maintenance costs can be avoided by proper maintenance management and adoption of well-thought maintenance policy. Indeed, degradation is an inevitable part of most production operations, which, if neglected, can lead to major faults and failures with significant impacts on the cost and availability of the production system. Therefore, maintenance and inspection activities should be planned in such a way as to prevent unexpected failures.

Preventive maintenance can be divided into two categories: time-based maintenance (TBM) and condition-based maintenance (CBM). Although TBM is easier to plan, CBM plans are generally more effective as they factor in the state of the components to be repaired. Basically, CBM is preventive maintenance based on condition monitoring. [3]. There have been many studies on maintenance strategies and specifically how to determine the correct time of maintenance activities. While failure-based maintenance is always overdue (in the sense that it is done after a failure occurs), preventive maintenance strategies such as age-based maintenance (ABM) are usually very conservative and lead to over-planning and over-doing maintenance. In

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comparison, CBM can be a more effective strategy because it delays maintenance activities as much as possible, but limits system failure by constantly monitoring certain indicators such as vibration and temperature. Despite this, most studies in the field of maintenance have been focused more on preventive maintenance policies than on CBM [4]. In a CBM plan, maintenance decisions are made based on the actual state of the system in a way that not only system lifetime is prolonged but also maintenance costs are reduced substantially. As shown in Fig1, CBM prevents unnecessary repair and maintenance by scheduling these activities based on the system state; a feature that makes CBM more efficient and less costly to implement than other maintenance strategies.

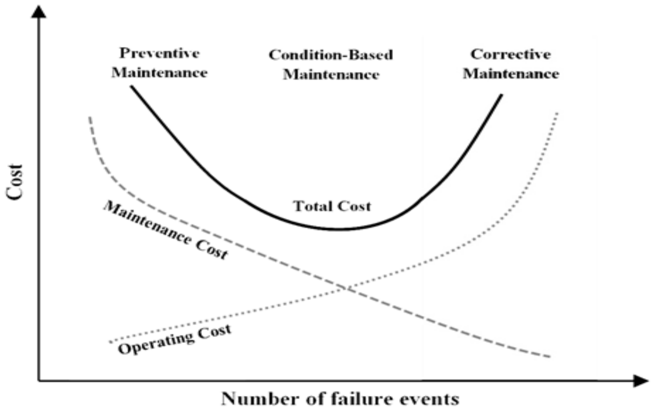

Fig. 1. Schematic diagram for operational, maintenance and total cost

By definition, CBM involves monitoring the health of the system being maintained. Thus, for CBM to be effective, the state of the system must be determined accurately. There are two ways to determine the state of a system: inspection and continuous monitoring. Recent advances in sensor technology have created ample opportunity for the continuous monitoring of a wide variety of indicators for CBM [5]. Sensors can trigger signals to draw attention to the state of the components they monitor, but they can also create false alarms because of measurement errors. Often, these errors are more frequent in highly complex systems, which require a large number of monitoring devices and equipment [6]. As a result, such systems are more prone to false alarms or false positive, i.e. receiving reports of fault when the system is actually healthy. Conversely, sensors may fail to detect a fault; a condition commonly known as returning false negative, which means receiving no indication of fault when the system is actually defective. A summary of the classification and terms used in this field is provided in Table 1 [7].

Tab. 1. Classification of system and inspection status [7]

Inspection outcome	System status	
	System good	System failed
Test says system good	True positive	False negative
Test says system failed	False positive	True negative

One reason why many maintenance policies fail in practice is that they are designed for single-component systems but are implemented for multi-component setups [8]. In a multi-component system, there may be three types of dependencies between components: economic dependency, stochastic dependency, and structural dependency. When there is an economic interdependence between components, it is cheaper to integrate maintenance activities than to do them for each component separately, especially if each activity has a fixed fee. The integration of repair and maintenance activities of multiple components is known as the clustering of maintenance activities or opportunistic maintenance, which often has huge cost-saving benefits [9]. The cost impacts of different maintenance activity clustering techniques have been researched extensively [10].

The goal of maintenance policies is to keep the system in safe working order at the lowest possible cost. Perfect maintenance operations that make the system as good as new are simple but often very expensive. In contrast, imperfect maintenance operations restore the system to a state that lies somewhere between "as good as new" state and the pre-maintenance state [11]. However, most of the models in the maintenance literature assume that maintenance will be perfect. In other words, they assume that maintenance intends to make the system as-good-as new, which could be a huge waste of resources. Among the several models that have been developed for imperfect maintenance, the (p, q) model has become quite popular because of its greater flexibility. In this model, it is assumed that after maintenance, the system may return to the "as-good-as new" (AGAN) state with probability p and to the "as-bad-as old" (ABAO) state with probability q (i.e. if minimum maintenance is done) [12].

A common assumption in many CBM models and studies is that the temporal distribution of component lifetime is known. But in practice, this temporal distribution is rarely known with certainty. This uncertainty has received attention from several researchers. In this regard, uncertainty can be divided into two categories: uncertainty in the model and uncertainty in the parameter. Several solutions have been proposed for both categories of uncertainty. A common approach is to assume a definite distribution with unknown distribution parameters (parameter uncertainty). This is a good approach as long as the chosen distribution is flexible enough to provide a good description of all types of failure [13]. As explained in Section 2, previous studies on the clustering of CBM activities have been focused on complex models that are difficult to implement in practice. This paper presents a simple clustering model that factors in the actual state of the system and can be easily implemented for any system.

In this paper, the effect of different maintenance clustering policies on the cost and availability of a multi-component system is investigated. The system has three states: normal, defective, and failed, with 5 degradation levels, which represent the progress of deterioration. Sensors are employed to determine the true state of the system while there exist errors in determining the system states by the sensors, i.e., there is a possibility of false alarm. Different levels for maintenance actions, e.g., perfect and imperfect actions, are assumed, and different scenarios for clustering maintenance actions are proposed and compared. The effects of uncertainty in lifetime distribution on the clustering of maintenance activities and the cost/availability optimization are examined. With the best of authors' knowledge, it is the first study that proposed a general method for clustering of condition based maintenance actions given the conditions and characteristics of the system described above.

The main advantages of the proposed method and model of this paper are summarized as follows:

- Development of a model for clustering maintenance actions given the real conditions so that the model can be implemented for different production systems and different working conditions.
- Considering the simultaneous effects of continuous monitoring and inspection in order to decrease the number of unnecessary inspections.
- Taking into account the imperfect maintenance actions, duration of maintenance actions, and uncertainty in determining the system states.
- Taking into account the two conflicting objectives: minimizing costs and maximizing availability.

2. Review of Literature

Maintenance refers to all activities that are done to keep the system in working condition or return it to optimal operating conditions. The purpose of CBM is to reduce unnecessary maintenance and eliminate the risks associated with preventive maintenance. There have been many studies on CBM models for multi-component systems, which have reported interesting results.

In [14], a CBM model was proposed for multi-component systems with economic dependency and an advanced algorithm was developed to reduce the cost of maintenance activities for a group of components. While this study provided a number of numerical examples, it did not provide an overview optimization policy. In [15], a series of prognosis methods were used to predict the remaining useful life in CBM. This paper also presented a dynamic predictive maintenance policy for cost-minimization in multi-component systems. After clustering the activities based on their economic and structural dependencies, the effect of imperfect maintenance on the system was investigated. For performance evaluation, this policy was applied to a numerical example and the results were compared with the results of other ABM and CBM policies. This comparison showed that the proposed model is significantly more effective in terms of cost-saving. However, this policy involves periodic inspections and does not factor in system availability. In [16], an integrated model of CBM and statistical process control is developed for a production process while the effect of maintenance is imperfect based on a stochastic geometric process. In [11], researchers introduced a CBM policy for the perfect and imperfect maintenance of a deteriorating system. The first goal of this study was to investigate the effect of imperfect maintenance activities with both positive and negative effects taken into account, and its second goal was to provide a maintenance policy that would specify whether perfect or imperfect maintenance should be done in each inspection. In this study, it was assumed that inspections are periodic and the time between every two inspections is determined based on the remaining useful life of the system. This model can be implemented for a single-component system where the sole purpose is cost minimization. However, availability maximization is also very important for both perfect and imperfect maintenance policies, and especially the latter, because although imperfect maintenance is less expensive, it may significantly hurt system availability. Therefore, it is preferable to try minimizing cost and maximizing availability simultaneously. In [17], a maintenance activity grouping policy was proposed for a system under continuous monitoring. In this study, it was assumed that the system is made up of dissimilar components with gradual degradation, meaning that they show signs of deterioration before completely breaking. In this policy, when the system degradation level exceeds the warning threshold, maintenance activities are grouped in such a way as to prevent system failure and improve availability. Furthermore, it was assumed that the entire system will be replaced upon reaching a certain age to meet safety requirements. A nonlinear, multivariate model was developed to simultaneously determine the optimal warning threshold for the subsystems and the replacement age. A shortcoming of this model is that it ignores the effect of the errors of the monitoring system and environmental shocks. In [18], a CBM policy was proposed for the multi-component systems with economic and stochastic dependencies. In this opportunistic maintenance model, components are maintained in groups because of their economic interdependencies. In this model, periodic inspection intervals are optimized independently for each component, and therefore probabilistic limits are used to decide how to cluster the component. In [19], researchers introduced a multilevel maintenance policy for a multi-component system with two independent failure modes. In this study, failures of all system components were divided into two modes: hard and soft. It was assumed that the system is continuously monitored and an imperfect alarm is triggered upon predicting a hard failure. On this basis, maintenance decisions in the presence of uncertainty were examined, and the benefits of continuous monitoring with different levels of uncertainty were identified. In this study, three types of maintenance strategies were considered: periodic, reactive, and opportunistic. It was assumed that periodic maintenance will be scheduled for each individual system at regular intervals, and between every two instances of periodic maintenance, reactive maintenance will take place based on an imperfect prediction signal. It was stated that in cases where maintenance activities are expensive or face practical limitations, reactive maintenance and periodic maintenance activities both provide an opportunity to perform maintenance operations on other components as well. In this study, only two modes of failure, i.e. soft and hard, were considered, and the alarm could only be triggered before hard failure. Also, this study ignored the possibility of sudden failure and assumed that all maintenance activities will be perfect (i.e. will make the system as good as new), which is not very realistic. In [20], a preventive maintenance activity grouping strategy was developed for a multi-component production system with economic interdependence between components. The objectives of this strategy were to minimize costs and maximize system availability. For this purpose, the Particle Swarm Optimization (PSO) algorithm was used to determine the best grouping of maintenance activities. In this study, maintenance was assumed to be perfect and the possibility of imperfect maintenance was ignored. In [21], researchers considered a multi-component system consisting of several identical units that requires a conservative maintenance strategy. In such systems, since delaying maintenance activities is not allowed, clustering activities can be beneficial in terms of cost-saving. After modeling system degradation, this study presented an opportunistic maintenance model with two simple systems with one or two signals for condition monitoring. This study aimed to determine when and how to cluster maintenance activities to minimize maintenance costs for the described multi-component system.

There have been many studies on maintenance policy optimization for systems with known lifetime distribution. While most studies assume that lifetime distribution and its parameters are known with certainty, this is not true in practice. In a study by De Jonge et al. [22], they investigated the effect of parameter uncertainty by examining how an age-based maintenance policy will be affected by considering a theoretical uniform distribution and a more realistic Weibull distribution. This study showed that considering uncertainty has a notable impact on the determination of optimal maintenance age and its costs. They stated that the results can facilitate maintenance decision making under uncertainty and help determine when it is worthwhile to invest in advanced data improvement procedures. De Jonge et al. [22] also developed a time-based maintenance plan for a repairable component with a limited lifespan for which the temporal distribution of life is uncertain. In that study, the unit was assumed to be in one of two possible states, weak or strong, each having its own life distribution. They considered the benefits of postponing preventive maintenance activities in the first phase of the unit’s life, and stated that although these delayed activities lead to higher maintenance costs, they provide additional information that leads to more efficient maintenance for the rest of the unit’s life. Some other studies have also considered this uncertainty in the system state detection. Brado et al. [23] proposed an inspection and replacement policy for a protection system in which the inspection process is error-prone and susceptible to false alarms. In this study, it was assumed that the state of the system (good or bad) is determined by imperfect inspections, which can produce both false positives and false negatives. Such imperfect tests are similar to those commonly used in quality control, screening procedures in medicine, and modern electronic systems, such as the latest automotive technologies to monitor oil levels, tire pressure, etc. In this study, Brado et al. developed two models: one where false alarms automatically lead to replacement, and another one where the decision regarding replacement is made after inspection. This study also considered the possibility of imperfect maintenance, i.e. replacing the defective component with a weak component. With this possibility, in the worst-case scenario, a false alarm can lead to the replacement of a healthy component with a weak component and therefore reduced system availability. In that study, it was assumed that inspections are periodic and therefore a failure occurring between two inspections could not be detected. Also, this model only applies to single-component systems and only for cost minimization objective, whereas availability is also very important. In a study by [24], he developed a CBM model in which the system has three states: perfectly healthy, defective, and failed. This study assumed that inspection is imperfect and has a constant chance to correctly detect the state, and once the system becomes defective, it takes a random period of time for it to fail. One of the shortcomings of this model is the periodic nature of inspections, which imposes extra costs and increases the failure rate. Further, this model assumes that it takes negligible time to repair or replace a component, whereas downtimes can lead to significantly reduced availability. This model also assumes that the system, whether healthy or not, is completely replaced in the n^{th} inspection.

The criteria most commonly used in CBM optimization models are cost, availability, reliability, and safety, which, in many cases, are in conflict with each other. For example, cost minimization often leads to unacceptably low availability or reliability. Therefore, to achieve an optimal maintenance policy, availability, reliability, and costs must be optimized simultaneously together. In a study by Kiu et al. [25], they provided an optimal maintenance and availability policy for a repairable system with multiple failure modes under periodic inspection. In this policy, upon encountering a failure mode, the system undergoes the corresponding corrective maintenance operation with random duration. This model determines the optimal inspection interval that maximizes availability and minimizes cost. Indeed, the analysis of availability, as an important indicator of system performance, is quite important for reliability estimations. While the availability of systems with a single failure mode has been the subject of many studies, a complex system can undergo multiple failure modes before its ultimate breakdown; an issue that has not received enough attention. In their study, Kiu et al. presented an availability model for a system with multiple failure modes. In that study, periodic inspections were used to identify system failures, as they are easier to plan. But these inspections were assumed to be perfect and error-free, which is not realistic. Furthermore, considering recent advances in sensor technology, condition-based inspection planning can be more effective. Also, while most industries typically use multi-component systems, Kiu’s model has been developed for single-component systems and can only be applied to systems where there is no interdependence between components. In [26] a mathematical maintenance model is presented in which a resource-saving strategy is made based on the use of technical diagnostics results. Calculations of the model are based on the probability of failure and operation in different conditions. This model is considered for a specific case and a general policy is not provided. Papu et al. [27] developed a hybrid maintenance model, in which only one component of the system is continuously monitored and when the time comes for it to be repaired, other components also receive opportunistic, preventive, or corrective maintenance. In this model, the maintenance operation starts when the system degradation level exceeds a threshold defined for the monitored component. This threshold is optimized to reduce the maintenance cost of the monitored component and the failure cost of other components. In this model, maintenance is assumed to be perfect, but monitoring is also considered to be perfect and error-free, which is unrealistic.

In multi-component systems, the term “structural dependence” refers to the situation where repairing or replacing one component will make it necessary to repair or replace another component. In contrast, stochastic dependence refers to the situation where the failure of a component is partially dependent on the state of one or more other components. Economic dependence means that the maintenance of a set of different components together costs differently than the maintenance of each individual component independently from others. In [28] a predictive maintenance model developed that can predict and warn for system failure by condition monitoring and comparing the previous and current situation. In [29], they developed a degradation state-space partitioning method for the opportunistic maintenance of multi-component systems with economic dependence. In this model, maintenance activities are assumed to be opportunistic, preventive, or corrective, and the limits of degradation state of each unit are used to decide whether or not maintenance is opportunistic. This model was presented by a single numerical example and only for a specific state and does not provide general approach for optimal policy. Oldkizer et al. [30] modeled the maintenance of a system consisting of three parallel components with economic dependency because of load sharing, failure dependency, and maintenance initiation costs. In this model, the system is formulated as a Markov decision process and optimal replacement decisions are made with the goal of minimizing costs per unit time. In this study, Oldkizer et al. provided a general representation of the optimal policy structure through numerical analysis and sensitivity analysis with respect to changes in the degree of load sharing and maintenance initiation costs and the degradation process. While this policy has been developed for relatively simple systems, it is difficult to implement for complex systems, and should therefore be considered for such systems. Also, this study assumed that maintenance time and planning time are negligible and inspections are carried out at regular intervals. Dewo et al. [31] proposed a CBM model for a two-component system with economic and stochastic dependencies. In this model, inspections are done with preventive and opportunistic policies and involve the replacement of damaged components. These researchers developed a cost model, in which economic dependence between components is considered, for determining the optimal value of decision variables. The results of this study showed that it is crucial to consider the dependence between components as ignoring this has significant cost implications. It was also reported that introducing an opportunistic replacement limit makes the maintenance policy more flexible and less sensitive to the inspection interval. The model of Dewo et al. has been developed for only two components and is not applicable to multi-component systems. Also, this model assumes that inspections are done at regular intervals.

Many studies have entirely focused on single-component systems. For example, Yang et al. [32] proposed a maintenance policy for a single-component system with two competitive failure modes, one based on system failure and the other based on shock failure. In this study, the degradation process was divided into three stages: healthy, defective and failed. It was assumed that random shocks occur according to a non-homogeneous Poisson process, leading to system failure, and that system degradation follows the Wiener distribution. In this model, inspections are performed periodically to measure the state and level of deterioration of the system, which is a time-consuming and costly process. In another study, Yang et al. [33] developed a preventive maintenance strategy for an industrial system with three states. The system has two failure modes: soft and hard. To prevent these failures, they provided a multi-stage maintenance policy that is combined with a replacement policy based on age and two-stage inspection. The results showed that this hybrid policy has lower maintenance costs than similar models that use one type of policy. In this model, imperfect maintenance was not considered, system degradation had only two modes, and multi-state and multi-component systems were not covered. Zhang et al. [35] investigated a three-state system with imperfect maintenance based on imperfect inspections with non-fixed probabilities, and proposed a replacement-repair-inspection policy for this system. This model has been developed for a one-component system and cannot be applied to a multi-component system. It also involves periodic inspection, which is a costly process.

In this study, we extend the clustering model presented by De Jonge et al. [21] into a hybrid CBM policy with imperfect maintenance and preventive replacement. Instead of a complex system depending on detailed condition monitoring information, we consider a simpler system with three levels of signal. With this policy, the clustering that minimizes cost per unit time can be determined based on system signals. Basically, instead of conducting optimization for a series of specific cases, we define the problem in a general form in order to reach a simple policy with applicability on any system. Table 2 classifies the most relevant studies to the current research in order to show the novelty aspects of our study. The differences between this study and other studies conducted in this field and the main contributions of the paper are summarized below:

1. Most models focus on cost minimization, neglecting the importance of availability maximization. Here, the goal is to determine the clustering that optimizes both cost and availability.
2. The impacts of imperfect maintenance and imperfect signals on the clustering of maintenance activities are discussed and the consequences of neglecting them in maintenance planning are illustrated.
3. The effects of uncertainty in lifetime distribution on the clustering of maintenance activities and the cost/availability optimization are examined.
4. The impacts of uncertainty in the system state detection process and the possibility of error in the signaling system on the clustering and optimization are investigated.
5. Unlike many studies that have ignored repair time and inspection time, these times and their effect on availability are considered in the model.

This study also considers the effect of clustering techniques on the maintenance costs for a set of systems with certain structures. Many previous studies have been focused on developing complex algorithms for maintenance modeling or solving such algorithms. One of the primary tasks in CBM modeling is the prognosis, which can be considered a relatively unexplored field of research in this area given the advances in monitoring technology. Considering the impact of state monitoring and clustering on the maintenance cost optimization, we assume that the condition monitoring system is given and triggers warnings based on defined limits, but there is some uncertainty in the system state detection because of environmental errors. The random distributions that determine when a component is at a particular stage of failure are estimated based on condition monitoring data, but our emphasis is not on determining these time distributions.

In Section 4, we begin with determining an exponential time distribution for system signals, for which there is uncertainty in the determination of parameters. This helps us gain an analytical view of the benefits of clustering. Section 5 is dedicated to the analysis of numerical results and section 6 presents the conclusions.

Tab. 2. Classification of the most related papers to the current study

	Objective function	Type of dependency	Maintenance policy	System failure mechanism	Effects of maintenance
[6]	Minimizing costs per time unit	-	CBM	Exponential distribution	Imperfect
[20]	Minimizing costs and maximizing availability	Economic	CBM	Gamma distribution	Imperfect
[11]	Minimizing costs per time unit	Economic	CBM	Discrete distribution	Perfect
[4]	Minimizing costs per time unit	Economic	CBM	Poisson distribution	Perfect
[25]	Minimizing costs per time unit	Economic and structural	CBM	Discrete distribution	Perfect

		dependency			
[15]	Minimizing costs	Stochastic and economic dependency	PM	Gamma distribution	Perfect
[35]	Minimizing costs	Structural dependency	PM	General continuous distribution	Perfect and Imperfect
Current study	*Minimizing costs And maximizing availability*	*Economic*	*PM and CBM*	*Exponential distribution*	*Perfect and Imperfect*

3. Problem Statement

$F(t,\lambda_i)$: distribution function of the exponential distribution with parameter λ_i

X_i:duration of the i^th warning in deterioration level i

λ_i: Warning rate in deterioration level i

C: fixed cost of maintenance

c: variable cost of perfect maintenance

h: maintenance time

D: required time for maintenance after a final warning (delay time)

R: the ratio

p : probability of good repair to AGAN state upon a repair

q : probability of minimal repair to ABAO state upon a repair

L_j: likelihood that $\lambda_i = \lambda_{ij}$

MC_N : the average cost per unit time in case of No clustering

MC_A : the average cost per unit time in case of clustering

P_i : initial probability that unit is weak

C_p : cost of good maintenance

C_{ir} : cost of minimal repair

C_{me} : cost of error maintenance

C_i : cost of inspection

C_{ii} : cost of additional maintenance

α, β : probabilities of false positive and false negative

In this section, we simulate a hypothetical system to examine the effect of different clustering policies on system cost and availability. This system has three states: normal, defective, and failed, with 5 degradation levels, which represent the progress of deterioration. Fig2 shows the process whereby a component changes from being normal (healthy) to being failed. This figure depicts the degradation curve for three independent failure modes. The progression of each failure may be accelerated by changes in working conditions, maintenance, or even the progress of other failures. The system starts in a healthy or as-good-as new (AGAN) state. In the normal state, the system works without any defects. In the as-bad-as old (ABAO) state, preventive replacement is done to restore the system to the AGAN state. In the defective state, the system is still operational but has a number of defects that need to be addressed.

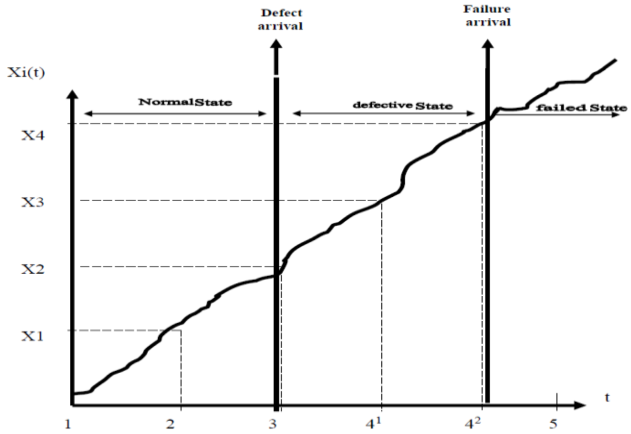

Fig. 2. The degradation behavior of the system

The basic assumptions made in the study of this system are listed below:

1) The as-bad-as old state becomes evident as soon as it happens and there is no error in recognizing this situation.

2) There is a monitoring system that triggers a signal whenever there is a change in the system state, but these signals are imperfect. There are two types of error in the signals: 1) false positive, 2) false negative. The probabilities of these errors are constant and are shown in Table 3.

3) Once the system is identified as defective (either correctly or because of a false positive), imperfect maintenance will be performed. When the system is truly defective, imperfect maintenance lead to one of the following situations:

- With probability p, the system returns to the AGAN state and incurs the cost C_p (good maintenance)
- With probability q, the system returns to the ABAO state and incurs the cost C_{ir} (minimal maintenance)
- With probability *1-p-q*, the system lapses into the failed state and incurs the cost C_{me} (error maintenance)

Tab. 3. Probabilities of different results by imperfect predication warning [34]

Predication warning result	System status	
	System normal	System defective
System normal	*1-α*	*β*
System defective	*α*	*1-β*

4) When the system is healthy (normal) but is falsely identified as defective, imperfect maintenance lead to one of the following situations:

- With probability $p+q$, the system returns to the AGAN state and incurs the cost C_p
- With probability *1-p-q*, the system lapses into the failed state and incurs the cost C_{me}

These probabilities are given in Table 4.

5) Once the system lapses into the failed state because of wrong maintenance, an immediate corrective replacement will be performed.

Tab. 4. Probabilities of state transitions before and after imperfect repairs [34]

Before repair	After repair		
	As good as new	As bad as old	Failed
Defect	*p*	*q*	*1-p-q*
False positive	*p+q*	*0*	*1-p-q*

Maintenance costs consist of fixed costs (*C*) and variable costs (*c*). The ratio of fixed costs to variable costs is denoted by *R* (*R=C/c*). Naturally, the higher the *R* ratio is, the better is the clustering. We consider three types of clustering policies. The "Alarm Clustering" policy involves repairing all the units for which the third warning (Alarm) is triggered. In this policy, repair should be done within a fixed period of length *D* after the Alarm. The "Alert (Signal) Clustering" policy involves repairing all the units for which an Alert (Signal) is triggered. The results of both of these clustering methods are compared with the results obtained without clustering (the "No Clustering" policy).

4. Derivation of the Equations for Different Clustering Policies

As mentioned in the previous section, the temporal distribution of alerts follows the exponential distribution with λ_1 , λ_2 , and λ_3 representing the Signal, Alert, and Alarm rates, respectively. In this study, we also assume that there some uncertainty in the degradation distribution parameter. For this purpose, it is assumed that with probability P_i, the unit to be repaired is weak and with probability $1 - P_i$, it is strong. The probability that the unit it weak (P_i,) is updated with a Bayesian method every time a maintenance activity is performed. We consider two types of time parameters: the time until preventive maintenance is called "censored duration" if maintenance is done before the maximum time x_3; the time until preventive maintenance is called "event duration" if maintenance is done exactly at x_3. Supposing that maintenance is done n times, the time of the k^{th} (k = 1, .., n) instance of maintenance is denoted by t_k. Here, $z_k = 1$ if i is an event duration and $z_k = 0$ if it is a censored duration. The prior Bayesian probability that the unit is weak is the initial probability *p*. We introduce $f(t:\lambda_i)$ as a density function and $F(t:\lambda_i)$ as an exponential distribution function with the parameter λ_i. The probability L_j where $\lambda_i = \lambda_{ij}$ and $j=1,2$ is given below:

$$L_j = \prod_{k=1}^{n}[F(t_k,\lambda_j)]^{z_k}[1 - F(t_k,\lambda_j)]^{1-z_k} \quad (1)$$

Therefore, the posterior Bayesian probability is:

$$p' = \frac{pl_1}{pl_1+(1-p)l_2} \quad (2)$$

The posterior Bayesian probability is used as the estimated probability that the unit is weak p'.
If the parameter λ of the exponential distribution is known with certainty, it is well known that the relative cost savings from clustering are:

$$CST(\lambda) = \frac{MC_N - MC_A}{MC_N} \quad (3)$$

Therefore where $\lambda = \lambda_1$ with estimated probability p', and where $\lambda = \lambda_2$ with estimated $1-p'$, the relative cost savings from clustering are:

$$CST^E = p'CST(\lambda_1) + (1-p')CST(\lambda_2) \quad (4)$$

In the following, we use a numerical example to compare the defined clustering policies in the presence and absence of uncertainty and with and without the possibility of imperfect maintenance. Here, State 1 indicates that the unit is in the AGAN state; State 2 indicates that the system is in the normal state but the Signal is triggered; State 3 indicates that the system is defective and the Alert is triggered; State 4^1 indicates that the system is defective and the Alarm is triggered but the system does not yet need to be repaired; State 4^2 indicates that the system is going to be replaced preventively. The state of the system is denoted by *(a, b)* where a is the state of the first unit and *b* is the state of the second unit. It is also assumed that the state *(a, b)* is equivalent to the state *(b, a)*.

No Clustering: In this policy, preventive replacement operation will be performed on each unit that falls in the state 4^2. In this policy, each unit receives maintenance independently. Therefore, the cost of each instance of maintenance is equal to the sum of fixed and variable costs. After replacement with probability *p* system returns to AGAN and with probability *q* remains in state ABAO. For each unit, the average time between two instances of maintenance is $\lambda_1 + \lambda_2 + \lambda_3 + D + h$. Therefore, the maintenance cost per unit time is:

$$MC_N = 2 * \frac{C + p(cp) + q(cir)}{\lambda_1+\lambda_2+\lambda_3+D+h} \quad (5)$$

Fig3 shows all the possible states of the assumed system. The time distributions for reaching a state and transitioning to another and the transition probabilities and calculations for two signals provided in De Jonge [21]. Naturally, when one of the states depicted at the bottom of Fig3 occurs, a preventive replacement takes place. Whether or not the second unit is repaired at the same time depends on the clustering policy.

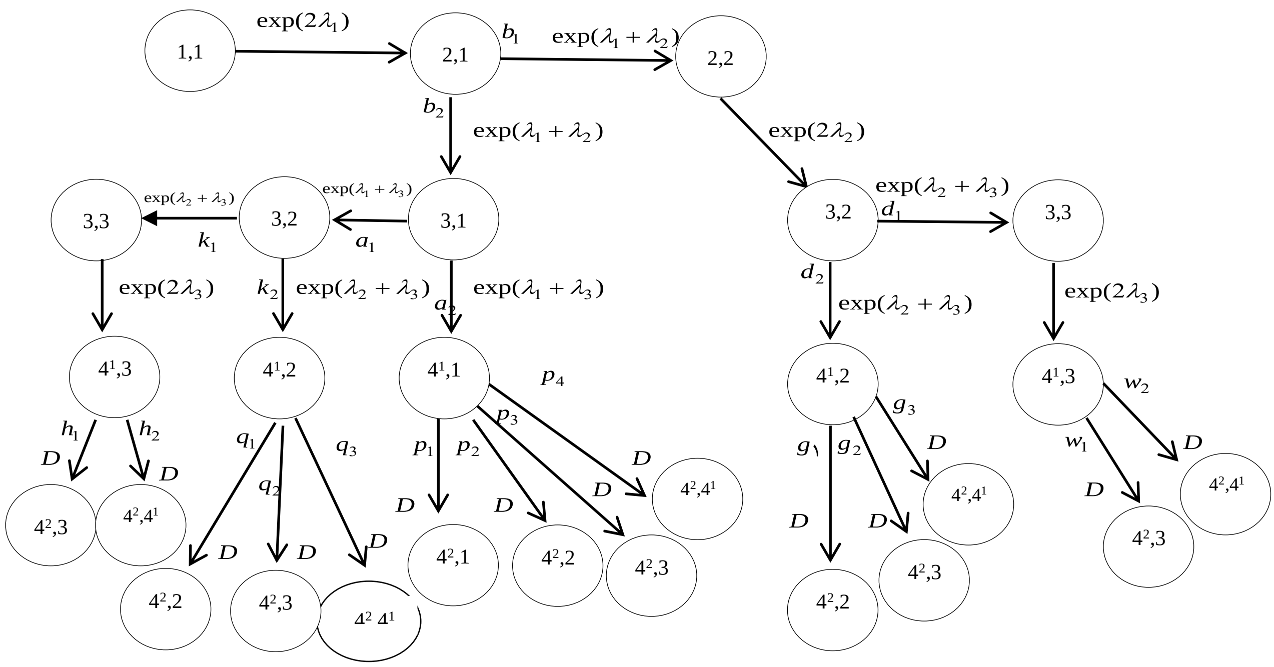

Fig. 3. State space of system with two units

Alarm Clustering: In this type of clustering, when the first unit is under repair, the second unit may trigger an Alarm. The unit will not be repaired if the Signal or Alert is triggered, but will be repaired otherwise (i.e. if the third warning is triggered). Since the predication signal system is prone to error, the system could be in State 4^1 and there is a β probability that being in this state does not trigger warning. In that case, the system will fail, incurring the cost C_f. If the system is in State 4^1, there is a *1-*β probability that warning will be correctly triggered, in which case one of the three defined types of maintenance will be performed on the second unit and the maintenance and inspection costs will be calculated accordingly. Therefore the cost of any maintenance is equal to:

$$A_{Alarm} = C + cp + \alpha c_i + (1-\beta) * (c_i + (b_2 a_2 p_4 + b_2 a_1 k_2 q_3 + b_2 a_1 k_1 h_2 + b_1 d_2 g_3 + b_1 d_1 w_2)(p)cp) + \beta(b_2 a_2 p_4 + b_2 a_1 k_2 q_3 + b_2 a_1 k_1 h_2 + b_1 d_2 g_3 + b_1 d_1 w_2)(1-p-q)c_f \tag{6}$$

If the state $(4^2, 1)$ or one of the states of $(4^2, 4^1)$ occurs, the system will reach state (1,1) after complete repair, otherwise it may return to state (1,3) or (1,2) because in situations other than $(4^2, 4^1)$ repair is only done on the first component. The probability of the system returning to state (1,1) equals:

$$b_2 a_2 p_1 + b_2 a_2 p_4 + b_2 a_1 k_2 q_3 + b_2 a_1 k_1 h_2 + b_1 d_2 g_3 + b_1 d_1 w_2 \tag{7}$$

With the same probability, the time between two maintenance actions involves an exponential distribution with the parameter $2\lambda_1$ between state (1,1) and (1,2). In addition, the time between two repairs always involves an exponential distribution with parameter of $\lambda_1 + \lambda_2$ and a constant time *D*. For the rest of the situations, we consider their times according to their probabilities. So the time between two maintenance actions is:

$$B_{Alarm} = \frac{1}{2\lambda_1}(b_2 a_2 p_1 + b_2 a_2 p_4 + b_2 a_1 k_2 q_3 + b_2 a_1 k_1 h_2 + b_1 d_2 g_3 + b_1 d_1 w_2) + \frac{1}{2\lambda_2} b_1 + \frac{1}{2\lambda_3}(b_2 a_1 k_1 + b_1 d_1) + \frac{1}{\lambda_2+\lambda_3}(b_1 + a_1 b_2) + \frac{1}{\lambda_1+\lambda_3} b_2 + \frac{1}{\lambda_1+\lambda_2} + D + h \tag{8}$$

Therefore, the average cost per unit time for Alarm clustering is:

$$MC_{Alarm} = \frac{A_{Alarm}}{B_{Alarm}} \tag{9}$$

Alert Clustering: When the first unit is under repair, the second unit may trigger an Alert. The unit will not be repaired if the Signal is triggered, but will be repaired otherwise. When the system is in State 3 or State 4^1, there is a *1-*β probability that an alert will be correctly triggered, in which case the system will incur maintenance and inspection costs. If the system is in State 4^1, there is a β probability that there will be no warning, leading to system failure. But if the system is in State 3, error in signaling will only impose an additional cost, which will be less than the cost of system failure. Therefore, the average cost of each maintenance activity is:

$$A_{Alert} = C + cp + \alpha c_i + (1-\beta) * (c_i + (1 - b_1 d_2 g_1 - b_2 a_2 p_2 - b_2 a_1 k_2 q_1 - b_2 a_2 p_1) * (pcp + qcir + (1-p-q)cme)) + \beta(b_1 d_2 g_2 + b_1 d_1 w_1 + b_2 a_1 k_1 h_1 + b_2 a_1 k_2 q_2 + b_2 a_2 p_3)cii + \beta\,(b_1 d_2 g_3 + b_1 d_1 w_2 + b_2 a_1 k_1 h_2 + b_2 a_1 k_2 q_3 + b_2 a_2 p_4)\, c_f \tag{10}$$

If the state $(4^2,1)$ or one of the states $(4^2,3)$, $(4^2, 4^1)$ occurs, the system returns state (1,1) after repair, otherwise it returns to state (2,1) and the probability of returning to state (1,1) equals to:

$$(1 - b_2 a_2 b_2 - b_2 a_1 k_2 q_1 - b_1 d_2 g_1) \tag{11}$$

With the same probability, the interval between the two repairs involves an exponential distribution with the parameter $2\lambda_1$. In addition, the time interval between the two repairs always includes an exponential distribution with parameter $\lambda_1 + \lambda_2$ and constant time *D*. So the average time between two repairs is:

$$B_{Alert} = \frac{1}{2\lambda_1}(1 - p_2 a_2 b_2 - q_1 k_2 a_1 b_2 - g_1 d_2 b_1) + \frac{1}{2\lambda_2} b_1 + \frac{1}{2\lambda_3}(b_1 d_1 + b_2 a_1 k_1) + \frac{1}{\lambda_1+\lambda_3} b_2 + \frac{1}{\lambda_2+\lambda_3}(a_1 b_2 + b_1) + \frac{1}{\lambda_1+\lambda_2} + D + h \tag{12}$$

So the average cost per unit time for Alert clustering is:

$$MC_{Alert} = \frac{A_{Alert}}{B_{Alert}} \tag{13}$$

Signal Clustering: When the first unit is under repair, there is an α probability that the second unit triggers the first warning, in which case one of the two types of maintenance defined for the normal state will occur. If the Signal is not triggered, there will be no cost or damage because the system is still in the normal state. Triggering of the second and third warnings, which can occur in State 3 and State 4^1 with a probability of $1-\beta$ will impose the maintenance and inspection costs on the system. If the system is in State 4^1, there is a β probability that there will be no warning, which will lead to the failure of the system. But if the system is in State 3, no signaling will only lead to incurring an additional cost. Therefore, the average cost of each maintenance activity is:

$$A_{Signal} = C + cp + \alpha * (b_1 d_2 g_1 + b_2 a_1 k_2 q_1 + b_2 a_2 p_2) * (c_i + (p+q)cp + (1-p-q)cme) + (1-\beta)(c_i + (1 - b_2 a_2 p_1) * (pcp + qcir + (1-p-q)cme)) + \beta(b_1 d_2 g_1 + b_2 a_1 k_2 q_1 + b_2 a_2 p_2)cr_2 + \beta(b_1 d_1 w_1 + b_2 a_1 k_1 h_1 + b_2 a_1 k_2 q_2 + b_2 a_2 p_3)cii + \beta(b_2 a_1 k_1 h_2 + b_2 a_1 k_2 q_3 + b_2 a_2 p_4 + b_1 d_2 g_3 + b_1 d_1 w_2)c_f \quad (14)$$

The interval between the two maintenance activities always includes an exponential distribution with parameter $2\lambda_1$, an exponential distribution with parameter $\lambda_1 + \lambda_2$ and a constant duration *D*. Other exponential distributions are considered with their related probabilities. So the average time between two maintenance activities is:

$$B_{Signal} = \frac{1}{2\lambda_1} + \frac{1}{2\lambda_2} b_1 + \frac{1}{2\lambda_3}(b_1 d_1 + b_2 a_1 k_1) + \frac{1}{\lambda_1+\lambda_3} b_2 + \frac{1}{\lambda_2+\lambda_3}(b_1 + a_1 b_2) + \frac{1}{\lambda_1+\lambda_2} + D + h \quad (15)$$

And the average cost per unit time clustering based on the first warning is:

$$MC_{Signal} = \frac{A_{Signal}}{B_{Signal}} \quad (16)$$

5. Policy Performance

This section, we evaluate the performance of the defined clustering policies and the No-clustering policy for different *p* and *c* values. These calculations have been performed using MATLAB. We also perform a sensitivity analysis by examining the effect of changes in each parameter on the expected cost while keeping the other parameter constant. The parameters and their values for sensitivity analysis are rationally selected according to the similar analyses conducted in related research. Fig4(a) shows the effects of changes in the probability pi (the probability that a unit is weak). It can be seen that for all pi values, the No-clustering policy costs more than all clustering policies. Among the defined clustering policies, Signal Clustering costs more than the other two policies, and this different widens as pi increases. This could be because in the Signal Clustering policy, preventive maintenance is done very quickly, and this imposes higher cost when the unit is weak. At higher pi values, there are larger differences between the results of clustering policies. It can also be seen that, for each given pi value, the Alert Clustering policy costs less than other policies and this cost difference becomes larger as pi increases. The effects of changes in the relative fixed maintenance cost (*R*) are illustrated in Figure (b). This figure also shows that the "No-Clustering" policy costs much more than other policies. As *R* increases, the Alert Clustering policy gets less costly than other policies, which could be because it contains more clusters than the Alarm Clustering policy. Also, in the Signal Clustering policy, preventive maintenance is done very quickly, which is very costly, and in the Alarm Clustering policy, maintenance is done late, which leads to incurring unexpected failure costs.

Figure (c) shows the effects of changes in p_i on system availability. This comparison shows that for all policies, the higher p_i value decreases the system availability. This may be because when the unit is weak, having a shorter average alert time results in a shorter time interval between two maintenance activities and therefore reduced system availability. The No-Clustering policy had a lower availability than all clustering policies. Among the defined clustering policies, Alarm and Alert perform almost identical in this respect and have lower availability than the Alert Clustering. This may be because, in the Alert Clustering policy, there are more clusters and also the alert is triggered when the system is defective, but in the Signal Clustering policy, although there are more clusters, the alert is triggered when the system is in the normal state.

Figure (d) shows the variations of system availability versus the maintenance time. When the maintenance time is zero, the defined policies perform almost identically and all yield maximum availability. But as the maintenance time increase, system availability decreases. Among the policies, Alert Clustering yields the highest availability, which is because of the greater number of clusters in this type of clustering.

In summary, the Alert Clustering policy performed better than the other two types of clustering in terms of both cost and availability, but this was expected because it involves a greater degree of clustering. In the Signal Clustering policy, maintenance operations are done too quickly, i.e. when the system is still in the normal state, which is not optimal in terms of cost and availability. We found that using other base values for cost and availability also yields similar results.

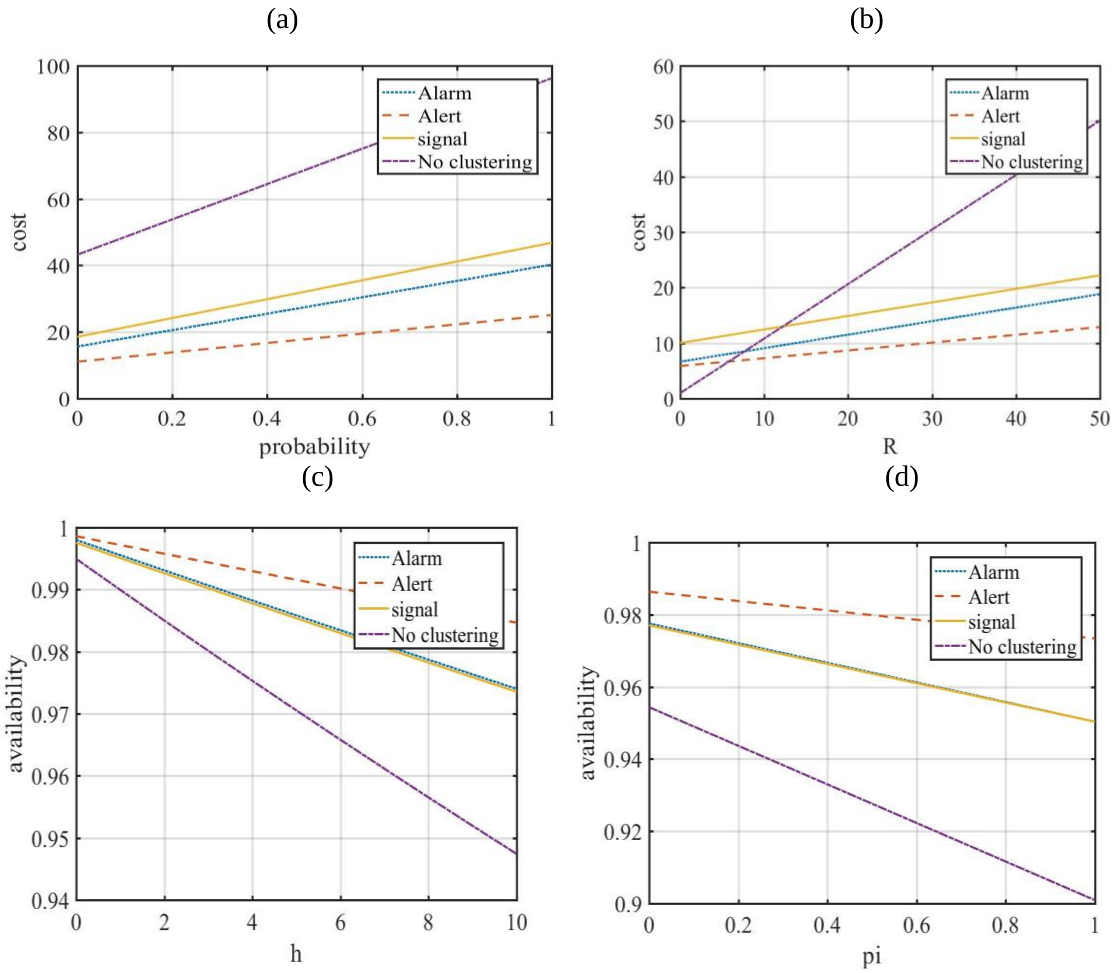

Fig. 4. Cost rate for clustering modes and no clustering based on different parameters
(a): effects of changes in the probability that a unit is weak on the costs, (b) effects of changes in the relative fixed maintenance cost (*R*) on the operational costs (c) effects of changes in p_i on the system availability, (d) the variations of system availability versus the maintenance time

Fig5 shows the percentage cost reduction under different clustering policies compared to the No-clustering policy as a function of relative fixed maintenance cost for different λ_i, w, p_i, α, and β values. Section (a) of Fig5 shows the percentage cost reduction for the base values specified below the figure. In sections (b), (c) and (d) of this figure, the value of the parameters is changed one by one, while keeping the probability of uncertainty at zero. Sections (e) and (f) of Fig5 shows the diagrams in the presence of uncertainty. Using other base values also produces similar results. For all the parameters investigated in Fig5, the Alert Clustering policy yields the highest cost savings. As expected, the average cost saving increases with the decrease in λ_i and α, β, but decreases as the maintenance time increases. In section (d) with increase in p and q, the average cost saving increases. Giving p_i a value decreases the cost-saving (relative to when weakness/strength of the unit is certain), and this decrease in cost-saving becomes larger as p_i increases. The results depicted in this diagram are summarized in Table 5. As the table shows, decreasing the values of errors leads to more cost saving. The similar trend is also observable for time of maintenance, the initial probability that unit is weak and the failure rate. On the other hand, increasing the values of p (p : probability of good repair to AGAN state upon a repair) and q (probability of minimal repair to ABAO state upon a repair), increases the value of cost saving.

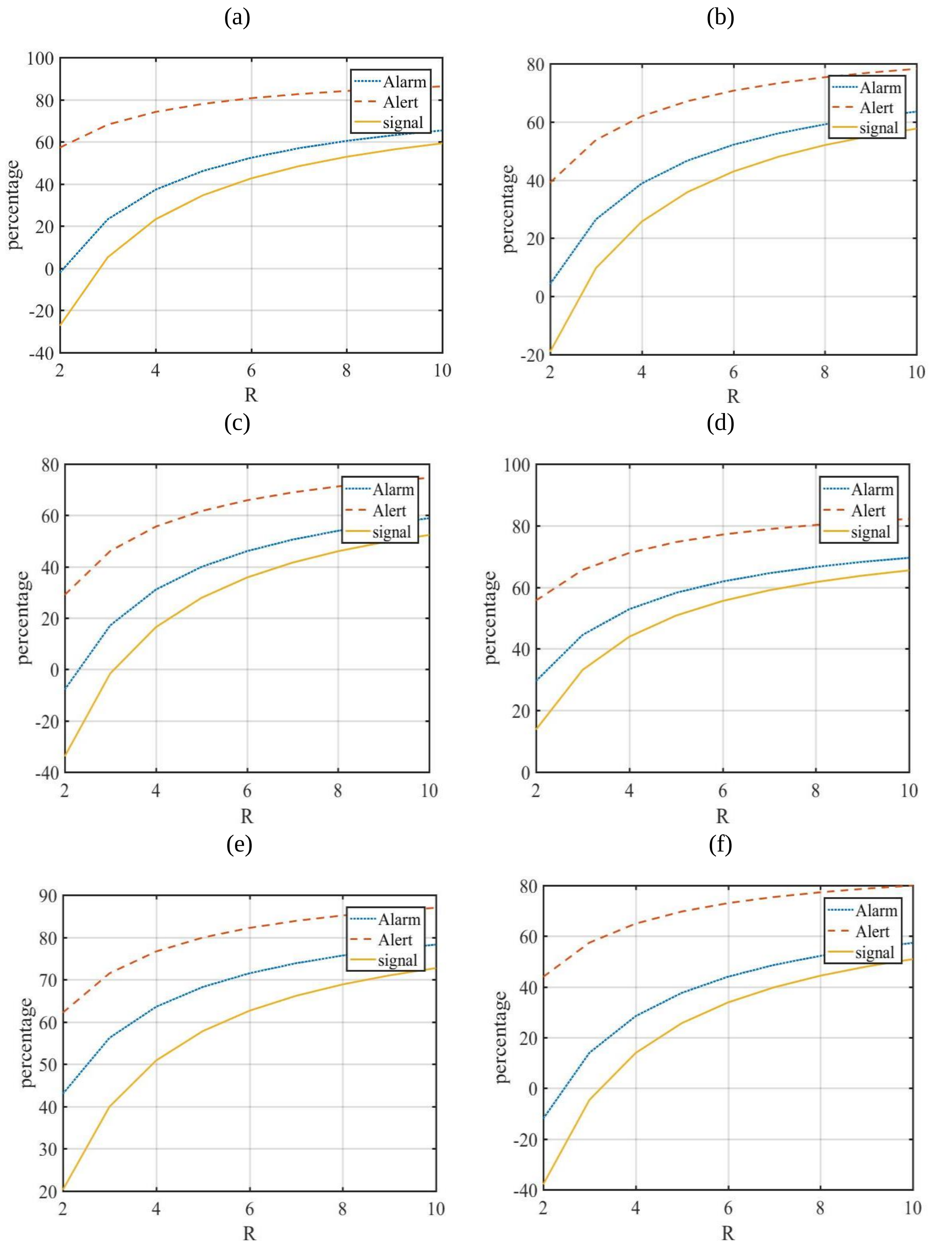

Fig. 5. Percentage decrease in cost clustering modes compared with No clustering (a) percentage of cost reduction for the base values, (b) effects of increasing $1/\lambda_i$ on the relative fixed maintenance cost (R), (c) effects of decreasing α , β on R, (d) effects of increasing maintenance time on R, (e) effects of increasing p , q on R for the base values and (f) effects of increasing p_i on R for the base values.

Tab. 5. The effect of changing the parameters on cost saving

Factor	Increasing $1/\lambda_i$	Decreasing α , β	Increasing time maintenance	Increasing p , q	Increasing p_i
Cost saving	Increasing	Increasing	decreasing	increasing	decreasing

6. Numerical Results

Here, we use a numerical example to illustrate the benefits of clustering policies in the presence and absence of uncertainty and with and without the possibility of imperfect maintenance for different α, β, λ, and p_i values. The values assumed for these parameters are based on cost differences between the situations where temporal distribution is certain and uncertain. We also tried to choose the parameter values rationally and based on real data used in other articles, though other data also produced similar results with only slight differences. The values considered for λ_i indicate that the highest cost saving can be achieved with the policy that combines imperfect maintenance with uncertainty (UI). Using lower λ_i values lead to lower cost-saving and vice versa. When the unit's weakness/strength is certain, p_i is either zero or one, and therefore $0 < p_i < 1$ only affects the costs when this variable is uncertain. Using the Bayesian method, p_i was estimated to 0.13 (in the examples, values less than that were set to 0.10 and values greater than that were set to 0.15). Ultimately, the preventive maintenance costs were assumed to be $C = 5,10,15$ in order to better illustrate the cost differences.

For this evaluation, we consider every combination of parameter values, which sum up to 14 combinations. For each of these combinations, we simulate 10,000 instances of maintenance operation in the uncertainty and imperfect maintenance (UI), uncertainty and perfect maintenance (UP), certainty and imperfect maintenance (CI), and certainty and perfect maintenance (CP) scenarios. The cost rates considered for this evaluation are shown in Table 6. The table shows the cost saving associated with each clustering policy. With respect to the parameters values, the cost rate is computed for each clustering policy (signal, alert, alarm) and no clustering policy in different scenarios (UI, CI, CP, UP). For example, according to the results of the table, for Case 1, UP-UI leads to 14.9% saving in the operational costs. In addition, for all cases, alert clustering policy leads to better performance with respect to the lowest cost.

As expected, the lowest cost is achieved in the CI scenario in each policy. The UP-UI column of this table shows the percentage cost saving that can be achieved by using imperfect maintenance instead of perfect maintenance. The results of this table are consistent with the results presented in Section 4. It can be seen that Alert Clustering, which is the cheapest policy, provides 14.9-33% cost saving relative to the UP scenario. As expected, the costs increase as the probability of error in the alarming system increases. For all clustering and No clustering policies, as the maintenance time increases, so does the maintenance cost. This is because as the delay time increases, so does the probability that the second unit fails and triggers an alert during this time, which will result in higher costs. A decrease in $1/\lambda_i$ also increases the cost because it decreases the average time to alert and therefore the time interval between two maintenance activities.

Tab. 6. Experiment results

case	$1/\lambda_1$	$1/\lambda_2$	$1/\lambda_3$	α	β	*pi*	*c*	*h*	*D*	clustering	UI	CI	CP	UP	Optimal clustering	UP-UI (%)
1	90	70	60	0.20	0.20	0.13	10	5	10	Signal	18.77	15.57	17.13	20.80	Alert	14.9
										Alert	12.85	11.03	12.61	14.77	clustering	
	40	30	20							Alarm	21.43	17.65	21.43	25.84		
										NO	49.77	42.93	43.22	50.11		
2	90	70	60	0.40	0.30	0.13	10	5	10	Signal	19.25	15.68	17.26	20.98	Alert	27.0
										Alert	11.91	10.79	12.93	15.13	Clustering	
	40	30	20							Alarm	20.91	17.62	22.07	26.55		
										NO	49.77	42.93	43.22	50.11		
3	90	70	60	0.20	0.20	0.13	10	5	15	Signal	18.88	15.66	17.28	21.01	Alert	15.1
										Alert	12.91	11.07	12.67	14.86	Clustering	
	40	30	20							Alarm	21.43	17.67	12.51	25.91		
										No	48.44	42.04	42.32	48.76		
4	90	70	60	0.20	0.20	0.13	10	5	10	Signal	18.26	15.25	16.77	20.23	Alert	15.8
										Alert	12.56	10.89	12.46	14.54	Clustering	

	40	30	20							Alarm	20.84	17.29	20.99	25.14		
										No	47.18	41.18	41.46	47.50		
5	90	70	60	0.20	0.20	0.25	10	5	10	Signal	21.71	15.25	17.13	24.19	Alert	15.3
										Alert	14.53	10.89	12.61	16.76	Clustering	
	40	30	20							Alarm	24.91	17.29	21.43	29.91		
										No	56.09	41.18	43.22	56.47		
6	90	70	60	0.20	0.20	0.10	10	5	10	Signal	18.03	15.57	17.13	19.95	Alert	14.8
										Alert	12.43	11.03	12.61	14.27	Clustering	
	40	30	20							Alarm	20.56	17.65	21.43	24.83		
										No	48.19	42.93	43.22	48.52		
7	90	70	60	0.40	0.30	0.10	10	5	10	Signal	18.29	15.57	17.26	20.12	Alert	29.5
										Alert	11.30	11.03	12.53	14.63	Clustering	
	40	30	20							Alarm	20.31	17.65	22.57	25.57		
										No	48.19	42.93	43.21	48.52		
8	90	70	60	0.40	0.30	0.10	10	5	15	Signal	18.42	15.61	17.41	20.32	Alert	22.8
										Alert	11.98	11.18	12.99	14.71	Clustering	
	40	30	20							Alarm	20.35	17.83	22.14	25.62		
										NO	46.96	42.04	42.32	47.28		
9	90	70	60	0.40	0.30	0.13	10	10	10	Signal	18.05	15.36	17.08	19.85	Alert	22.9
										Alert	11.81	11.08	12.85	14.52	Clustering	
	40	30	20							Alarm	20.04	17.64	21.84	25.23		
										NO	46.96	42.04	42.32	47.28		
10	90	70	60	0.40	0.30	0.25	10	5	10	Signal	22.05	15.57	17.41	24.41	Alert	23.1
										Alert	13.94	11.03	12.99	17.17	Clustering	
	40	30	20							Alarm	24.54	17.56	22.14	30.81		
										NO	56.09	42.93	42.32	56.47		
11	90	70	60	0.40	0.30	0.25	10	5	15	Signal	22.22	15.61	17.41	24.67	Alert	23
										Alert	14.05	11.18	12.99	17.29	Clustering	
	40	30	20							Alarm	22.58	17.83	22.14	30.85		
										NO	54.35	42.04	42.32	54.71		
12	80	60	50	0.40	0.30	0.13	10	5	10	Signal	24.37	18.00	19.88	27.46	Alert	16.1
										Alert	15.16	12.41	14.24	17.60	Clustering	
	30	20	10							Alarm	27.61	20.38	24.87	33.68		
										NO	60.12	49.18	49.51	60.52		
13	90	70	60	0.20	0.20	0.13	15	5	10	Signal	42.33	26.22	26.67	49.21		33
										Alert	24.53	16.98	23.04	32.78	Alert	
	40	30	20							Alarm	46.08	26.49	39.12	62.86	Clustering	
										NO	90.18	64.39	64.83	90.78		
14	90	70	60	0.20	0.20	0.13	5	5	10	Signal	10.25	08.16	09.24	11.05	Alert	20.5
										Alert	06.88	04.52	05.30	08.29	Clustering	
	40	30	20							Alarm	11.24	7.43	08.39	14.91		
										NO	30.06	21.46	21.61	30.26		

7. Conclusion

In multi-component systems with economic dependency, repairing multiple components together, which is called opportunistic maintenance or maintenance clustering, is more cost-effective than repairing each component independently from others. The majority of past studies on CBM activity clustering have provided complex algorithms for this purpose without enough attention to system availability and without considering the possibility of imperfect maintenance. In this study, we considered a three-state system with imperfect maintenance, imperfect alerting, and uncertainty in the time distribution of the alerts. A CBM activity clustering policy was developed by combining inspection and state monitoring tasks. Then, a sensitivity analysis was performed on the model parameters and the system availability was discussed with the help of diagrams and several numerical examples. By analyzing the changes in the optimal policy, we found that considering the uncertainty in the temporal distribution of lifetime and the possibility of imperfect maintenance is critical for effective maintenance management. Under the assumption of certainty (in lifetime distribution) and perfect maintenance, cost and availability only depend on the number of alerts and maintenance activities, but under the assumption of uncertainty and imperfect maintenance, cost and availability are also influenced by the quality of the alerting system and imperfect maintenance. After examining the impacts of considering uncertainties in lifetime distribution and system state and the possibility of imperfect maintenance in maintenance clustering, we found that:

- If there is reasonably reliable information about the maintenance cost and the system degradation process and there is a mechanism available to monitor the system state, the model presented in the paper can be used to avoid costly inspections and carry out maintenance activities according to the system state.

- In cases where there are uncertainties in the system state detection (the alerting system is imperfect), insisting on having perfect maintenance can substantially increase maintenance costs, because expensive perfect maintenance can be wasted on the repairs that are not needed.
- In choosing the optimal maintenance clustering policy, it is important to consider not only cost minimization but also availability maximization. Based on this approach, the diagrams and numerical analyses of this study showed that among the defined policies, Alert Clustering provides the best results in terms of maintenance cost and system availability. The cost-saving achieved with this policy was as great as 80% (compared to no clustering). In comparison, the Alarm-Alert Clustering policy achieved about 60% cost saving. Using other numerical values also yielded similar results.
- In most cases, the temporal distribution of the lifetime of a unit is not known with certainty, but if this distribution is known, maintenance can be done at a much lower cost because then the maintenance plan must only factor in the error of the alerting system. However, uncertainty in the rate of alerts increases the likelihood of error, ultimately leading to an error in choosing the time and level of maintenance.

Limitations of the proposed method, which can be considered for development of the current study, can be stated as follows. A two-component system with identical units is assumed in this study. Development of this study for more complex systems, i.e. systems with many components and large-scale systems, and using reinforcement learning algorithms to solve the derived models are worth investigating as a future work. Moreover, conducting the proposed methods for systems with non-identical components is worth investigating. Another limitation of this study is that the probabilities of error were considered constant. Hence, study the effects of variable error probabilities is also a fruitful direction for development of the current research. As a final limitation of the research, assuming unlimited time horizon can be mentioned. Relaxing this assumption in order to employ the method for a finite horizon is another promising avenue for the extension of the current method.

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