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Multi-level opportunistic predictive maintenance for multi-component systems with economic dependence and assembly/disassembly impacts

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Abstract: For maintenance optimization of multi-component systems, opportunistic maintenance has been addressed in many studies since it allows considering the advantages of dependences between components in maintenance decision-making process. In the literature, economic dependence, which implies that joint maintenance of several components can reduce the maintenance cost, has been widely studied in the framework of opportunistic maintenance. There are however very few existing studies considering the advantages of structural dependence, whereby maintenance of a component requires disassembly of other components, in maintenance optimization. To face this issue, the objective of this paper is to propose a multi-level opportunistic predictive maintenance approach considering both economic and structural dependence. In that way, the economic and structural dependences between components are firstly formulated. A degradation model considering disassembly impacts is then developed. For opportunistic maintenance decision-making, two opportunistic thresholds are introduced. When corrective/preventive maintenance occurs, the first opportunistic threshold (eR_o) is defined to select non-disassembled components for opportunistic maintenance. This first opportunistic decision allows considering the economic dependence between components. In addition, the maintenance of the selected components may require disassembly of other components which could be also good candidates to be opportunistically maintained. So, the second opportunistic threshold, sR_o ($sR_o \geq eR_o$), is then developed to select one or several disassembled components to be opportunistically maintained. To evaluate the performance of the proposed opportunistic maintenance approach, a cost model is developed. Particle swarm optimization algorithm is then applied to find the optimal decision variables. Finally, the proposed opportunistic maintenance approach is illustrated through a conveyor system to show its feasibility and added value in maintenance optimization framework.

Key words: *Multi-component system; structural dependence; economic dependence; opportunistic maintenance; maintenance optimization.*

1. Introduction

Maintenance cost takes a significant proportion (15-70%) in the overall operation cost of the manufacturing systems [1]. Therefore, minimizing the maintenance cost could increase the competitiveness as well as the productivity of the industrial companies. Over the last decades, companies and scholars have been seeking for advanced maintenance strategies with possible lowest cost and/or downtime [2]. Predictive maintenance (PdM) is a potential candidate. PdM considers the current state incorporating with the prognostic information of the components' health in maintenance decision making. Therefore, it can increase the probability that the maintenance actions are placed at right time just before failure, leading to

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decrease in the overall maintenance cost and downtime [3]. Generally, PdM consists of three processes: (1) condition monitoring, (2) degradation modeling and prediction and (3) maintenance decision-making and optimization. The condition of the system can be monitored through inspection actions, which can be conducted continuously or discretely. Based on the monitoring condition and historical degradation data, the degradation process is modeled and future condition of the system can be predicted. This predicted information plays an important role in maintenance decision-making and optimization process [4].

However, manufacturing system has become more and more complex, i.e., it consists of multi-interdependent components. The dependences between components significantly influence the maintenance decision making process, leading to the demand of new maintenance decision making rules taking into account the dependences between components. Indeed, these dependences can be classified into three main categories: economic, stochastic, and structural dependences [5,15]. The economic dependence implies that joint maintenance of a group of components is either cheaper (positive economic dependence) or more expensive (negative economic dependence) than maintenance these components individually [35]. The economic dependence has been widely studied in literature due to its direct impact on maintenance decision-making and optimization process through maintenance cost [5, 15]. Recently, grouping maintenance strategies have been proposed in [6,8,36,37] to take advantage of positive economic dependence between components, i.e., the sharing of maintenance setup cost. Stochastic dependence occurs when the state of a component influences lifetime distribution of other components [5,9]. To take into account the stochastic dependence between components, several opportunistic maintenance approaches have been proposed to promote the degradation interactions between components in both degradation process and maintenance decision process [9-11]. Finally, structural dependence applies in situation where components structurally form a connected set, and the repair or replacement of a component requires disassembly of other components. It means that to reach a component for maintenance, other obstructing components, which block the disassembly path of the maintained component, must be disassembled [5,12,13]. Although, structural dependence broadly applies in practice, there is however very few works that considered structural dependence in maintenance optimization [15].

Early studies on maintenance for multi-component systems with structural dependence focus on replacement policy [44, 45]. In these studies, it is suggested that the system is built in a vertical structural of groups of components, and replacing a component at a higher level requires replacing all the components at its lower level. The problem is whether to replace the whole system or replace a sub-assembly or just a single component when that single component failed. Zhou et al. (2015) considered a more realistic model given the relationships of components in a hierarchical structure, where the components can have relationships with others at both higher and lower levels and at the same level [12]. An opportunistic maintenance model is then proposed to take advantage of structural dependence. In this model, minimal repair is applied when component is failed and preventive maintenance is applied if the reliability of the component reaches the preventive maintenance threshold. A time window T_w is proposed to consider other components for opportunistic maintenance. If a maintenance occurs (corrective or preventive) at time t_k , other components that have the optimal maintenance time within the period $[t_k, t_k + T_w]$ is also opportunistically replaced. The hierarchical structural model is then extending to the selective

maintenance framework for multi-state system with structural dependence in Dao and Zuo (2016) [13]. Jia (2010) divided a multi-component system into m modules and assumed that replacing a component requires dismantling all components in the same module [46]. So the structural dependence results in the shared disassembly and re-assembly components. The shared disassembly and re-assembly cost can be considered as maintenance setup cost. Therefore, the structural dependence is usually considered as a part of economic dependence. Horenbeek and Pintelon (2013) added another cost element to setup cost to represent the structural dependence [47]. A grouping maintenance strategy for multi-components system with structural and economic dependences is proposed in Iung et al. (2015) [14]. The structural dependence between components is modeled by taking into account the disassembly duration saving when the components are maintained together. The purpose is to choose a group of components for maintenance having the highest saving cost which is including saving setup cost and saving disassembly duration. The limitation of these studies is to simplify the concept of structural dependence so that it can be treated using a single cost parameter, which is the same for all components. Moreover, these studies assumed that the disassembly operations for maintenance do not impact on the degradation process of components. However, this assumption is not always true in reality. Indeed, for maintaining a component, several other components need to be disassembled and the disassembly operations may also cause some undesired damages on the disassembled components [15, 16]. Currently, the impact of disassembly operations on the degradation/failure process of the disassembled components has been studied in [17, 18]. The disassembly operations play a role like a shock to disassembled components and affect the degradation and failure rate of the disassembled components, i.e., disassembly operations could result in an amount of damage on the degradation of the disassembled components. Although these two studies considering the disassembly operations impact on the degradation and failure rate of the components, the maintenance approaches proposed in these studies do not fully allow considering the advantages of structural dependence in maintenance decision-making and optimization.

In that way, to consider both structural and economic dependences in maintenance optimization for multi-components system, two main challenges are identified: (1) degradation modeling considering disassembly operation impacts and (2) adaptive maintenance decision-making rules and optimization process characterizing the properties of both the structural and economic dependences. For multi-component system optimization, opportunistic maintenance approaches are efficient methods since maintenance of a component offers a great opportunity to consider other component for maintenance. However, to the best of our knowledge, the existing opportunistic maintenance approaches do not directly allow to deal with the two mentioned challenges. Indeed, in the literature, the conventional approach for opportunistic maintenance is usually based on two different maintenance thresholds for preventive and opportunistic maintenance [18-23]. The first threshold is to identify components on which preventive maintenance can be applied. If a preventive maintenance (PM) or corrective maintenance (CM) occurs, the second threshold is used to select component for opportunistic maintenance (OM). A component is correctively or preventively maintained when it fails or when its reliability reaches the preventive maintenance threshold (R_p) respectively. When PM or CM occurs, other components are considered for opportunistic maintenance if their reliability reaches the opportunistic maintenance threshold R_o ($R_o \geq R_p$).

However, these approaches equally consider all components for only one opportunistic maintenance threshold. Therefore, it does not allow considering the advantages of the structural dependence. Indeed, to reach the components for PM or/and CM, some of components need to be disassembled while the others do not. It means that two categories of components should be specified for opportunistic maintenance selection: disassembled components and non-disassembled ones. The non-disassembled components raise only economic dependence, since they can share only setup cost, while the disassembled components promote not only economic dependence but also structural dependence hence providing more benefit for opportunistic maintenance, because they can share not only the setup cost but also disassembly duration, i.e., saving downtime cost. Therefore, using the same opportunistic threshold for all components does not allow fully considering the structural dependence between components.

To face these issues, in this paper a multi-level opportunistic maintenance approach is proposed to promote the advantages of both structural and economic dependence between components in maintenance decision-making and optimization. In that way, the economic and structural dependence between components are firstly formulated. A degradation model considering disassembly impacts is then developed. To select surviving components to be maintained, one preventive threshold and two opportunistic thresholds are herein proposed. The preventive threshold, denoted R_p , is used to select the components for preventive maintenance, i.e., a surviving component is selected to be preventively maintained if its predicted reliability is not higher than the preventive maintenance threshold R_p . If corrective/preventive maintenance occurs, the economic dependence-based opportunistic threshold, eR_o ($eR_o \geq R_p$), is defined to select one or several remaining components for opportunistic maintenance. This first opportunistic maintenance decision allows considering the economic dependence between components. The maintenance of the selected components may require disassembling other components which could be also good candidates to be opportunistically maintained. The structural dependence-based opportunistic threshold, sR_o ($sR_o \geq eR_o$), is then developed to select disassembled components to be opportunistically maintained. This second opportunistic threshold allows promoting the structural dependence, i.e., the setup cost and downtime cost saving. In that way, the proposed multi-levels opportunistic maintenance approach promises to be more profitable in considering both economic and structural dependences in maintenance optimization. It however requires more maintenance decision variables to be optimized regardless to conventional opportunistic maintenance approaches. To assess the performance of the proposed opportunistic maintenance approach, a cost model is also developed. For maintenance optimization, exhaustive search methods can be used to find the optimal maintenance decision variables, but the computing time is exponential with the number of decision variables [36, 37]. Particle Swarm Optimization (PSO) algorithm is an efficient optimization method to reduce the computing time of the optimization problem. PSO has been widely applied to optimization problems due to its advantages of simple operations, rapid searching, and promise to approach the global optimum [40]. In addition, the PSO has shown its feasibility in maintenance optimization in several studies [41-43]. So, in this study, PSO is implemented to find the optimum decision variables. Finally, the proposed opportunistic maintenance approach is illustrated through a conveyor system to show its feasibility and added value in maintenance optimization framework.

In relation to these contributions, the rest of the paper is organized as follows. Section 2 presents the modeling of the degradation process of the system's components when considering the structural dependence between components. Economic dependence between components is also formulated. The proposed multi-level opportunistic maintenance policy is then described in section 3. A cost model and a maintenance optimization process are also presented. A numerical example of conveyor system is carried out in section 4 to illustrate the feasibility and the advantages of the proposed maintenance approaches. Different comparisons studies with a conventional opportunistic policy are herein investigated. Finally, some conclusions and potential future works are presented in section 5.

ABBREVIATIONS

PdM	Predictive maintenance
PM	Preventive maintenance
CM	Corrective maintenance
OM	Opportunistic maintenance
eOM	Economic dependence-based opportunistic maintenance
sOM	Structural dependence-based opportunistic maintenance

NOTATION

n	Number of components of the system.
c^s, C_i^c, C_i^p	Setup cost, corrective and preventive cost of component i
H_i	Impact of disassembly operations on the degradation process of component i
α_i, β_i	Scale and shape parameters of the gamma degradation process of component i
$f_{\alpha_i(t-s), \beta_i}$	Probability distribution function associated to the degradation process of component i
$X_i(t)$	Degradation level of component i at time t
$\Delta X_i(t-s)$	Incremental in the degradation level of component i during $(t-s)$ time unit
L_i	Failure threshold of component i
$G_{CM/PM}^z$	Group of components for PM or/and CM at the inspection z^{th}
τ_i, τ_{G^k}	Maintenance duration of component i and group G^k respectively
τ, R_p	Inter-inspection interval and preventive threshold respectively
eR_o, sR_o	Economic dependence-based and structural dependence-based opportunistic threshold respectively
$R_i(t)$	Reliability of component i at time t
$R_i(T_{z+1} x_i^z)$	Conditional reliability of component i at time T_{z+1} given its degradation level at time T_z is x_i^z

2. Assumptions and manufacturing system modeling

Consider a multi-component system, consisting of n interdependent deteriorating components. Each component is subjected to an accumulative continuous degradation (underlying degradation process), which can cause random failure. Such a process may be physical health indicators, such as accumulation wear, crack growth, corrosion, etc., or synthesized health ones which are built from different measurements [3,23,24,29]. The degradation process of each component assumes to evolve stochastically and gradually

over time. Therefore, the degradation level of each component i ($i=1,2,\dots,n$) can be described by a scalar random variable $X_i(t)$. Component i is considered as failed when its degradation level exceeds its critical threshold (or failure threshold), L_i .

To avoid the components/system failure and restore the system when the failure occurs, both corrective maintenance (CM) and preventive maintenance (PM) are considered. PM is defined as a maintenance action performed on a surviving component, i.e., the degradation level of the component is lower than its failure threshold. CM is applied when a component is failed, i.e., its degradation level is higher than its failure threshold. Either PM or CM is applied, maintenance action brings the maintained component to “as good as new” state. It is assumed however that either PM or CM maintenance action can be carried out only at regular discrete times at which inspection operations are realized. Also, only one maintenance team is considered to execute all maintenance operations. It should be noticed that when multi-repairmen are available, the total maintenance duration can be significantly reduced [36].

From physical point of view, components in the system are interconnected in multiple levels of hierarchical structure. A stoppage of each component due to failure or preventive maintenance actions, leads to a shutdown of the whole system, i.e., the components are a series structure from reliability block diagram (RBD) [34].

2.1. Degradation modeling

In the literature, there are several models proposed for modeling the degradation process of the components. Among them, gamma process is the most popular one [24,29,44]. Indeed, gamma process is a monotone increase stochastic process with independent and non-negative increment having a gamma distribution with an identical scale parameter. Hence, it is useful to describe the degradation process caused by the accumulation of wear, creep, fatigue, corrosion, etc. [24, 29]. Therefore, in this study, gamma process is used to model the degradation process of the system’s components. In that way, without any maintenance intervention, the increment in the degradation level of each component follows a gamma process. An illustration of a gamma degradation process is shown in Fig. 1.

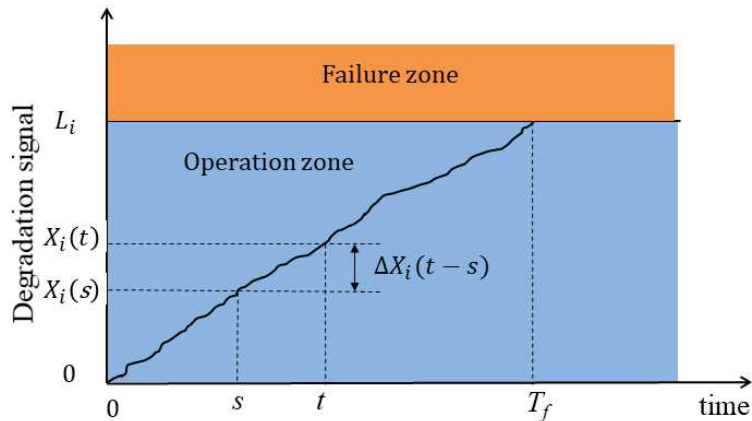


Fig. 1. Illustration of the degradation process of component i [24]

In that way, the degradation level of component i at time t , $X_i(t)$ can be expressed as:

$$X_i(t) = X_i(s) + \Delta X_i(t - s) \quad (1)$$

Where $\Delta X_i(t-s)$ follows a gamma distribution with shape parameter $\alpha_i(t-s)$ and scale parameter β_i , its probability distribution function is defined as:

$$f_{\alpha_i(t-s),\beta_i}(x) = \frac{1}{\Gamma[\alpha_i(t-s)]} \beta_i^{\alpha_i(t-s)} x^{\alpha_i(t-s)-1} e^{-\beta_i x} \quad (2)$$

Where, $\Gamma[t] = \int_0^\infty u^{t-1} \exp(-u) du$ is the Euler gamma function. The parameters of gamma stochastic process can be estimated from historical data [29,30]. In this study, it is assumed that the parameters of the gamma process for each component are known in advance.

2.2. Maintenance cost and economic dependence modeling

Performing a PM on surviving component i ($i = 1,2,\dots$) incurs a preventive maintenance cost, C_i^p , which can be divided into three parts.

$$C_i^p = c^s + c_i^p + c_i^d, \quad (3)$$

where,

- c^s represents logistic cost or preparation cost, which is associated with different actions such as, travelling maintenance team to the site, setup scaffolding, etc. c^s is called also maintenance setup cost. This cost is considered to be cost-independent of the maintenance operation nature and can be shared when several components are maintained together. In the literature, the setup cost represents the economic dependence between components [4,7,15]. In this study, we consider the case that only one setup cost is required when several components are maintained together. Note that this is also commonly considered in previous works in the framework of maintenance optimization for multi-component system, see for instance [2,4,15,35,44].
- c_i^p is a specific preventive cost including the component spare part and delivery cost.
- c_i^d is the downtime cost that incurs due to the loss of production during maintenance of component i . This cost may depend on both the downtime cost rate, denoted c^d , due to the stoppage of the system and the maintenance duration, denoted as τ_i , that can be divided into two parts: replacement duration (τ_i^r) and disassembly duration (τ_i^d). More precisely, c_i^d can be expressed as follows:

$$c_i^d = c^d \cdot \tau_i = c^d \cdot (\tau_i^r + \tau_i^d) \quad (4)$$

It is important to note that the disassembly duration τ_i^d can also be shared if maintenance on a component j ($j \neq i$) requires a disassembly of component i . This is due to the structural dependence between two components (more details on structural dependence are presented in Section 2.2).

Similarly, if component i is failed, the corrective maintenance is executed and incurs a corrective maintenance cost:

$$C_i^c = c^s + c_i^c + c_i^d \quad (5)$$

where, c_i^c is a specific corrective cost including spare part cost, delivery cost of component i and also cost related to damage caused by the failure of component i . Therefore, the specific corrective cost is likely to be more expensive than specific preventive cost ($c_i^p < c_i^c$).

Note that as maintenance actions can be performed only at inspection time, if a component fails before the next inspection, an additional cost is incurred due to the performance loss caused by the system downtime until the next inspection epoch at a cost rate c^{lost} .

It is now considered the case whereas a group of several components, denoted group G^k , that are jointly maintained. The setup cost of the group can be shared thanks to the sharing of economic dependence between components. Consequently, the total maintenance cost of G^k can be defined as follows:

$$C_{G^k} = \sum_{i \in G^k} [C_i^c \cdot I_i^c + C_i^p \cdot (1 - I_i^c)] - (|G^k| - 1) \cdot c^s - \Delta\tau_{G^k} \cdot c^d \quad (6)$$

Where,

- I_i^c is the indicator function, $I_i^c = 1$ if corrective maintenance is executed on component i , $I_i^c = 0$ otherwise.
- $|G^k|$ is the number of components in group G^k and $(|G^k| - 1) \cdot c^s$ represents the total setup cost saving when jointly executing the maintenance of group components G^k . To consider the economic dependence between components in maintenance decision-making, an opportunistic maintenance decision rule is developed in Section 3.
- $\Delta\tau_{G^k}$ is the total maintenance duration saving when group of components G^k are maintained together (see section 2.3). Indeed, $\Delta\tau_{G^k}$ is related to the fact that maintenance on a component may require a disassembly of other components. Therefore, the disassembly duration may be shared.

2.3. Structural dependence modeling and disassembly impacts

2.3.1. Structural dependence modeling

From the physical structure point of view, the components in the system form a hierarchical structure with multiple levels. Each level may consist of several components or groups of components. There exists a disassembly sequence between components/groups of components. The precedence relations govern the order of disassembly of components, which is graphically represented by directed graph [12,13]. The directed graph utilizes nodes to represent the components/sub-assemblies and directed and undirected lines to present the disassembly precedence between components. There are three different types of nodes: root node, denoted as "0", represents the system; intermediate nodes, presented by a letter, represent the sub-assemblies; and leaf nodes, denoted by a number, represents the component lowest level. [The line connecting the nodes in different levels represents "father-son" relationship between two nodes. It indicates that to reach the node in lower level \(the "son" node\), the node in upper level \("father" node\) needs to be disassembled first.](#) The line connecting the nodes in the same level may be directed (line with arrow) or undirected (straight line without arrow). The directed line represents the disassembly sequence between components. The undirected line between components in the same level means that the components are mutually restricted, and disassembly of a component always means disassembly of the other.

As an example, consider a conveyor system which is shown in Fig.2. The conveyor system consists of two subsystems, driving system and transporting system. The driving system is composed of drive motor

and gearbox. Drive motor connects to the gearbox through coupler 1. The transporting system is composed of a belt, head and tail pulleys and bearings. The driving system connects to the transporting system through coupler 2.

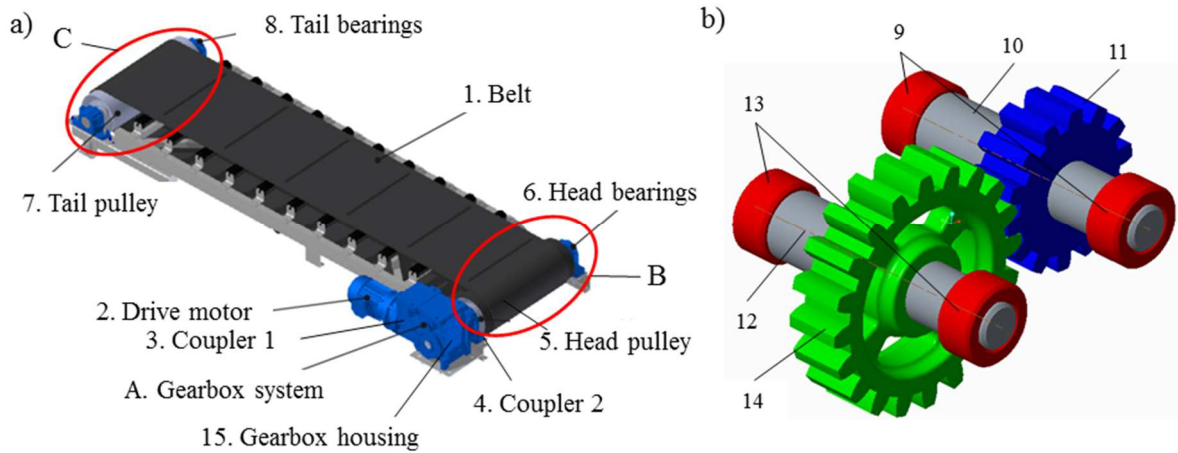


Fig. 2. (a)-Conveyor system and (b)-its gearbox A

The directed graph of the conveyor system is sketched in Fig. 3.

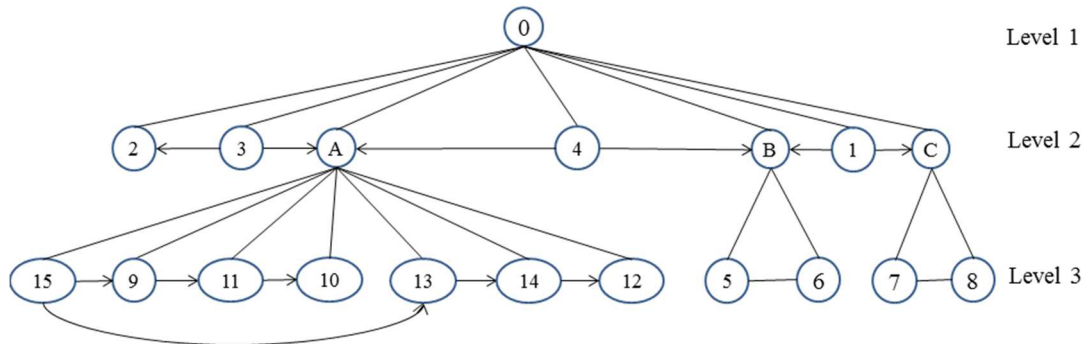


Fig. 3. Directed graph of the conveyor system

From the directed graph, we can define the disassembly path of the components for maintenance, i.e., which components need to be disassembled to reach the maintained components. For example, disassembly the component 5-Head pulley requires disassembly of the components 1-Belt, 4-Coupler 2 and 6-Head bearings. The disassembly matrix, $D = [D_{ij}]_{n \times n}$, is proposed to mathematically identify the disassembly path of the components. The elements of the disassembly matrix have the value of “0” or “1”. $D_{ij} = 1$ if component j is on the disassembly path of component i , i.e., to reach component i for maintenance, component j needs to be disassembled; $D_{ij} = 0$ otherwise; $D_{ii} = 1$ implies that for maintenance of component i , component i itself has to be also disassembled. In that way, the row i^{th} of the matrix D presents the disassembly path of component i . Reconsider the above example, the disassembly matrix of the conveyor system is shown in Fig. 4. Disassembly of component 5-Head pulley is defined by line 5 of matrix D in Fig. 4, where it indicates that component 1-Belt, 4-Coupler 2 and 6-Head bearings and component 5-head pulley itself are on disassembly path of component 5-head pulley.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
5	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0
6	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0
7	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0
8	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0
9	0	0	1	1	0	0	0	0	1	0	0	0	0	0	1
10	0	0	0	1	1	0	0	0	1	1	1	0	0	0	1
11	0	0	0	1	1	0	0	0	1	1	1	0	0	0	1
12	0	0	1	1	0	0	0	0	0	0	0	1	1	1	1
13	0	0	1	1	0	0	0	0	0	0	0	0	1	0	1
14	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1
15	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1

Fig. 4 Disassembly matrix of the conveyor system

2.3.2. Impacts of disassembly operations on maintenance duration

Consider that a group of components G^k that is jointly maintained. Since only one maintenance team is available, the total replacement duration remains unchanged when jointly performing maintenance on several components. The total maintenance duration saving on group G^k corresponds to the total disassembly duration saving of the group which can be evaluated as follows:

$$\Delta\tau_{G^k} = \sum_{j=1}^n \tau_j^d \cdot \max(\sum_{i \in G^k} D_{ij} - 1, 0) \quad (7)$$

Where, $\sum_{i \in G^k} D_{ij}$ is the total number of components in group G^k for which component j is on their disassembly path, i.e., total number of times that component j is disassembled if the components in group are maintained separately.

Eq.(7) implies that the total maintenance duration can be reduced when several components are maintained together. In addition, the structural dependence may also have an important impact on the degradation process of components [17,18].

2.3.3. Impacts of disassembly operations on degradation process

For a system with structural dependence, maintenance of a component requires disassembly of other components. Disassembly operations play a role like a shock to the disassembled components. The impacts of shock on the degradation process have been studied widely in literature [31-32]. However, the impact of shocks on degradation of the components presented in the previous studies assumed that shocks impact on all components. Recently, the impacts of shock on the degradation process due to the disassembly operations when conducting maintenance on other components have been investigated in [17, 18]. Indeed, the shock due to disassembly operations may lead to an increase in degradation level of the disassembled components. It is also shown in [17,18] that the impact of disassembly operations on the degradation process of a disassembled component may depend on various factors such as the strength of the connection between components, the properties of the components and the degree of expertise of technician and tools suitability [17]. As suggested in [17], the impact of disassembly operations on the degradation process of

the component when it is disassembled for maintenance of other components can be modeled by a half-normal distribution. In that way, in this work, it is assumed that the increment on degradation level of a disassembled component i due to the maintenance of other components, denoted as H_i , is described by a half-normal distribution with parameters $H_i \sim HN(\mu_{Hi}, \sigma_{Hi})$. More precisely, the probability density distribution of the half-normal distribution [33] is:

$$f_{\sigma_{Hi}\mu_{Hi}}(x) = \sqrt{\frac{2}{\pi}} \frac{1}{\sigma_{Hi}} e^{-\frac{1}{2}\left(\frac{x-\mu_{Hi}}{\sigma_{Hi}}\right)^2} \cdot I(x) \quad (8)$$

Where, $I(x) = 1$ if $x \geq \mu_{Hi}$ and $I(x) = 0$ otherwise.

Note that μ_{Hi} and σ_{Hi} are the mean and standard deviation of the based-normal distribution of the half normal distribution. The means (μ) and standard deviation (σ) of the half-normal distribution are:

$$\mu = \mu_{Hi} + \sigma_{Hi} \sqrt{2/\pi} \quad (9)$$

$$\sigma = \sigma_{Hi} \sqrt{1 - 2/\pi} \quad (10)$$

It should be noted that μ_{Hi} and σ_{Hi} can be estimated from a given dataset by several methods such as the method of moments or the method of maximum likelihood [17].

Suppose that between the two executive epochs s and t , a group G^k of several components are maintained separately, the degradation level of component i between the two executive epochs s and t can be expressed as:

$$X_{Hi}(t) = X_i(s) + \Delta X_i + \sum_{j \in G^k} D_{ji} \cdot H_i \quad (11)$$

Where, $X_i(s)$ is the degradation level of component i at time s ; ΔX_i is the increment of degradation of component i due to the inherent degradation process between two epochs s and t ; D_{ji} is the element (j,i) of the disassembly matrix, which indicates whether or not component i is on disassembly path of component j ; H_i is the impact of disassembly operations on the degradation process of component i . The degradation process of components i considering disassembly impact is illustrated in Fig. 5.

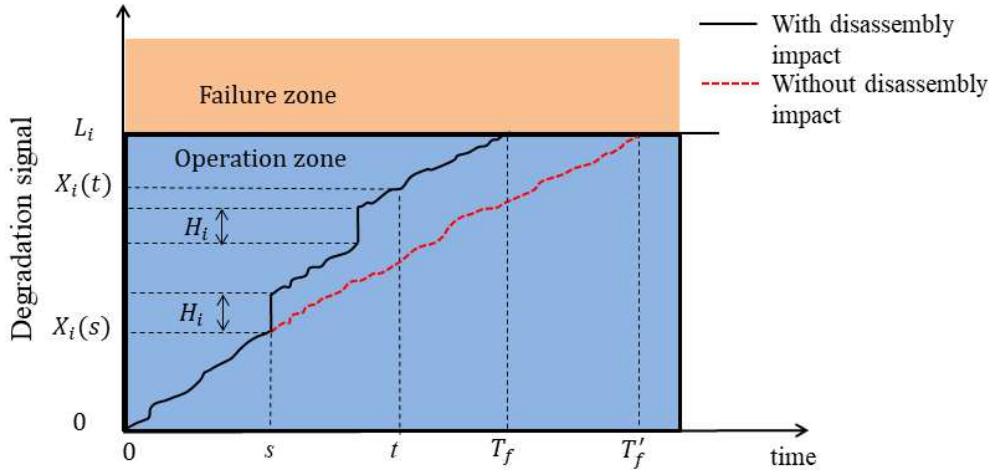


Fig. 5. Illustration of a degradation process considering disassembly operations impact

When conducting maintenance on a group of several components, there may be intersections among the disassembly paths of different components. It implies that component i may be on the disassembly path of several components. The shock due to disassembly operations only impacts on the disassembled components, i.e., the components on the disassembly path of the maintained components, and component is impacted once it is disassembled. Therefore, suppose that between the two executive epochs s and t , a group G^k of several components are maintained at the same time, i.e., component i is disassembled one time for maintenance of the whole group, the degradation level of component i between the two executive epochs s and t can be expressed as:

$$X_{Hi}(t) = X_i(s) + \Delta X_i(t - s) + H_i \cdot \max(D_{ji}), j \in G^z \quad (12)$$

Eq. (12) implies that if component i is not on the disassembly path of group G^k , i.e., it is not disassembled for maintenance of group G^k , hence, it is not impacted due to the disassembly operations for maintenance of group G^k . On the contrary, if component i is on disassembly path of one or several components of the group G^k , component i is affected due to the disassembly operations for maintenance of group G^k . However, the impact occurs only one time even the component i is on disassembly path of several components. It implies that grouping maintenance can reduce disassembly operations impacts. Moreover, the intersections among disassembly path of different components also imply that grouping maintenance can also save maintenance duration, since the disassembly duration can be saved. It provides a good opportunity for executing maintenance on the disassembled components. Considering the structural and economic dependences in maintenance decision-making requires to develop adaptive opportunistic maintenance rules, which is proposed in Section 3.

3. Multi-level opportunistic predictive maintenance policy

Predictive maintenance is the extension of condition-based maintenance, by considering the maintenance decision is based on the prognostics information/indicators related to the future evolution of the system's health condition given the current system state, the historical data and the future operation profile [2,55]. In that way, there are two main useful prognostics indicators [50,52,53]: (1)- the time left before the failure occurs (called remaining useful life -RUL) and (2)-the probability that the system operates without failure up to a given future time (conditional/predictive reliability). Most of predictive maintenance using RUL indicator has been proposed for single-component system. Indeed, RUL is conventionally considered as the individual indicator of each component and not necessary synchronized with other components and the whole system. Recently, this specific consideration has been extended/developed for multi-component system [51-53]. This orientation is relevant because predictive maintenance using the conditional/predictive reliability for maintenance decision-making has been extensively studied for multi-component system [2, 47, 49]. One of the advantages of this approach is that conditional/predictive reliability can be estimated at both component and system level giving a flexibility in maintenance decision-making (multi-level decision), see [2,23]. More details on the use of RUL and predictive reliability for predictive maintenance decision-making are discussed in [53]. In our work, we use the conditional/predictive reliability for predictive maintenance decision-making.

In the framework of predictive maintenance, two following features of maintenance modeling are considered [54]: (1)-Condition monitoring scheme and (2)-Maintenance decision making rule. In our study, it is assumed that the system's components are inspected at regular time $T_{z=z\tau}$, ($z=1,2,\dots$), τ is the inspection interval and a decision parameter needs to be optimized. Inspection is considered to be instantaneously and can perfectly reveal the degradation level of the components. At each z^{th} inspection epoch, degradation level of the components is measured by an inspection operation. The degradation level of component i at the z^{th} inspection epoch is denoted as x_i^z . Component i is considered as failed when its degradation level exceeds its critical threshold, i.e., $x_i^z \geq L_i$. Based on the degradation information, reliability of the component at the next inspection epoch is predicted. Based on the predicted reliability of the components at the next inspection epoch, maintenance decision at the inspection epoch z is made. [More detail about the maintenance decision making rule is presented in section 3.2.](#)

3.1. Reliability prediction

The reliability $R_i(t)$ of component i at time t is defined as the probability that component i is in functioning state between time 0 and t [34]. For a gradually deteriorating component, reliability is the probability that its degradation level $X_i(t)$ is still below a given failure threshold [35], and can be expressed as:

$$R_i(t) = P[X_i(t) \leq L_i] \quad (13)$$

Where, $X_i(t)$ is the predicted degradation level of component i at time t ; L_i is the failure threshold component i .

Consider that component i is functioning at inspection epoch z , (time T_z), and its degradation level is x_i^z . As mentioned in Section 2, the degradation level may be affected by disassembly operations, to evaluate the predictive reliability of a component, the components of the system are classified into two subsets: non-disassembled components and disassembled ones.

If component i is not disassembled at time T_z , its predictive reliability at the next inspection epoch ($z+1$) (time T_{z+1}), given its degradation level at time inspection epoch z is defined as:

$$\begin{aligned} R_i(T_{z+1}|x_i^z) &= P[X_i(T_{z+1}) \leq L_i|x_i^z] = 1 - \int_{L_i-x_i^z}^{\infty} f_{\alpha_i,\tau,\beta_i}(x)dx \\ &= 1 - \frac{\Gamma[\alpha_i,\tau,\beta_i(L_i-x_i^z)]}{\Gamma[\alpha_i,\tau]} \end{aligned} \quad (14)$$

Where, $\Gamma[\alpha_i,\tau]$ is the gamma function and $\Gamma[\alpha,\vartheta] = \int_{\vartheta}^{\infty} x^{\alpha-1}e^{-x}dx$ is the upper incomplete gamma function. The predictive reliability, $R_i(T_z|x_i^z)$, will be used as a criterion for preventive and opportunistic maintenance decision-making of non-disassembled components.

If component i is disassembled at inspection z^{th} for the maintenance of several components (group G^z), due to the disassembly operations impact, the degradation level of component i is increased by an amount of H_i . The predicted reliability of the component i considering disassembly operations impact can be expressed as:

$$\begin{aligned} R_i(T_{z+1}|x_i^z, G^z) &= P[X_{Hi}(T_{z+1}) \leq L_i|x_i^z, G^z] = 1 - \int_{L_i-(x_i^z+H_i)}^{\infty} f_{\alpha_i,\tau,\beta_i}(x)dx \\ &= 1 - \frac{\Gamma[\alpha_i,\tau,\beta_i(L_i-(x_i^z+H_i))]}{\Gamma[\alpha_i,\tau]} \end{aligned} \quad (15)$$

The predicted reliability considering disassembly impact will be used for opportunistic maintenance decision-making of disassembled components.

3.2. Description of multi-level opportunistic predictive maintenance policy

The main objective of the proposed maintenance policy is to find one or several components to be opportunistically maintained when maintenance (corrective and/or preventive action) on one or several components is needed at each inspection time. In that way, the maintenance decision process at the z^{th} inspection epoch is divided into 3 steps: (1) *CM/PM maintenance selection*, (2) *Economic dependence-based opportunistic selection (eOM decision)* and (3) *Structural dependence-based opportunistic selection (sOM decision)* as illustrated in Fig. 6.

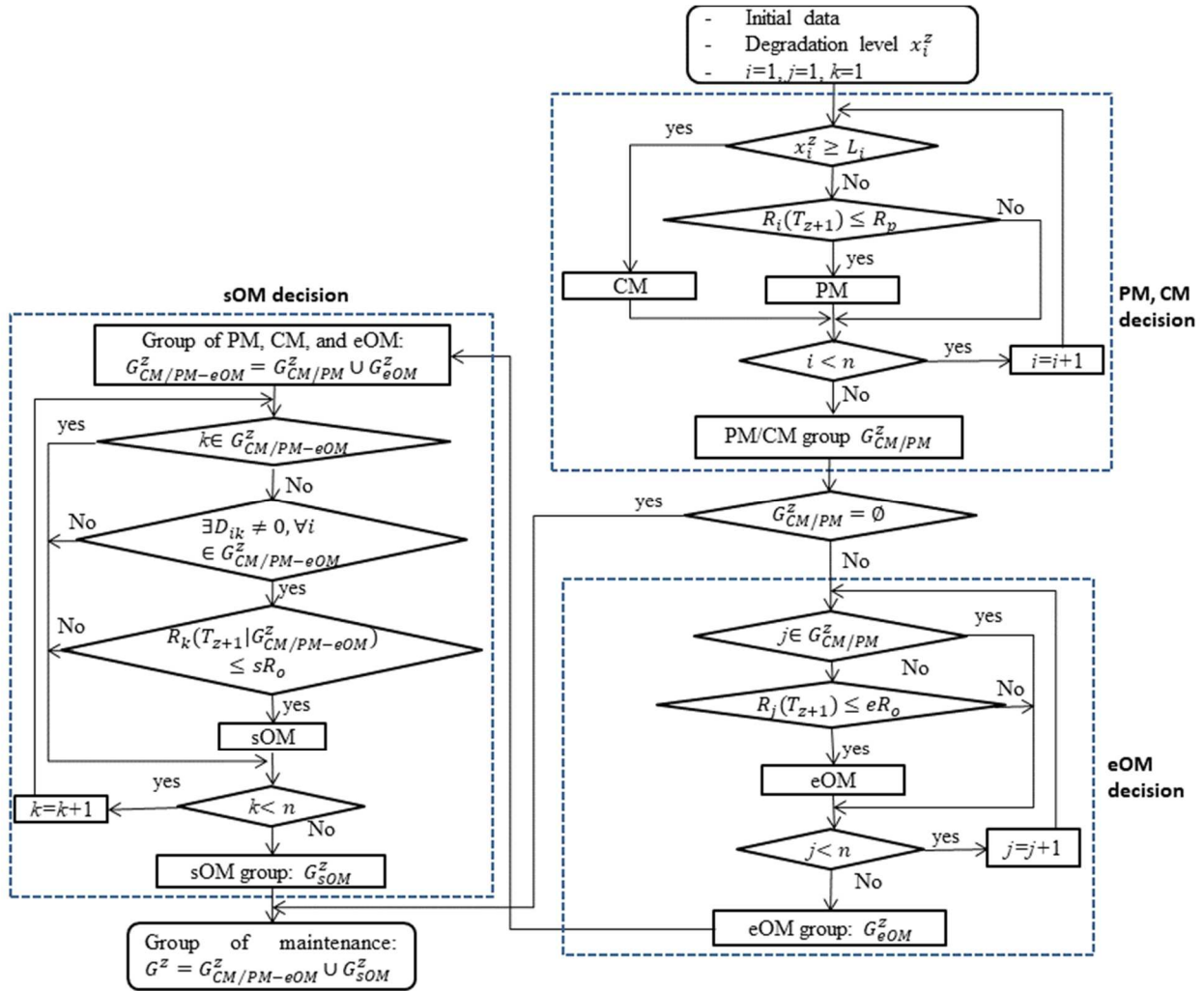


Fig. 6. Illustration of the maintenance decision process at inspection epochs

In Step 1 – *CM/PM maintenance selection*: Two cases are herein considered:

- If a component is failed between T_{z-1} and T_z , the failed component needs to be correctively maintained at time T_z .
- If no failed component is revealed between T_{z-1} and T_z , the degradation levels of all surviving components are firstly measured. The predictive reliability of each surviving component at the next inspection epoch (T_{z+1}) is then evaluated. Component i (with $i=1,2,\dots,n$) is selected to be

preventively maintained at T_z if its predicted reliability at T_{z+1} is below the preventive maintenance threshold, R_p ($R_i(T_{z+1}|x_i^z) \leq R_p, 0 \leq R_p < 1$), (R_p is a decision variable to be optimized).

The results of this step can be specified into two cases:

- If no maintenance action (corrective or preventive action) is identified, step 2 and 3 should not be activated. This means that no maintenance action is required at the z^{th} inspection epoch.
- If a corrective or preventive maintenance action on one or several components is needed, it may offer an opportunity to maintain other surviving components to take the advantages of dependence between components. One important issue is that opportunistic maintenance on several components can reduce the maintenance cost and/or duration thanks to the economic and/or structural dependence between these components (see sections 2.2 and 2.3).

In that way, if a group of several components, denoted group $G_{CM/PM}^z$, are selected to be maintained after step 1. To find other surviving components to be opportunistically maintained with the maintenance of group $G_{CM/PM}^z$ to take the advantages of economic dependence between components, step 2 has to be done.

Step 2-*Economic dependence-based opportunistic selection (eOM decision)* aims at addressing only the economic dependence on maintenance opportunistic maintenance decision making. A surviving component i ($i \in \{n \setminus G_{CM/PM}^z\}$) is selected to be economically maintained with group $G_{CM/PM}^z$ at time T_z , if its predictive reliability is below a threshold eR_o , called economic dependence-based opportunistic threshold eR_o , i.e., $R_i(T_{z+1}|x_i^z) \leq eR_o$ with $R_p \leq eR_o < 1$. eR_o is a decision variable which needs to be optimized. After this step, a component/group of components, denoted group G_{eOM}^z , may be selected for opportunistic maintenance together with group $G_{CM/PM}^z$. The opportunistic threshold eR_o is approaching R_p when the economic dependence is small.

Let $G_{CM/PM-eOM}^z$ be the set of all selected components from steps 1 and 2, i.e.,

$$G_{CM/PM-eOM}^z = G_{CM/PM}^z \cup G_{eOM}^z \quad (16)$$

It is important to note that the maintenance of group $G_{CM/PM-eOM}^z$ may need to disassembly other components which are classified into the subset Ω^D :

$$\Omega^D \cap G_{CM/PM-eOM}^z = \emptyset \quad (17)$$

To take the advantages of structural dependence between the disassembled components and group of components $G_{CM/PM-eOM}^z$, one or several disassembled components should be also opportunistically maintained at time T_z .

Step 3 - *Structural dependence-based opportunistic selection (sOM decision)* aims to find one or several disassembled components (components in Ω^D) to be opportunistically maintained together with group $G_{CM/PM-eOM}^z$. Thereby, a second opportunistic threshold sR_o , called structural dependence-based threshold, is herein introduced for opportunistic maintenance decision. Indeed, if the predicted reliability of a disassembled component i is below the structural dependence-based opportunistic threshold sR_o , i.e., $R_i(T_{z+1}|x_i^z, G_{CM/PM-eOM}^z) \leq sR_o$, disassembled component i is selected to be opportunistically maintained at time T_z . sR_o is a decision variable which needs to be optimized. It is reasonable to assume that $eR_o \leq sR_o < 1$ since the opportunistic maintenance of the disassembled components can save not

only setup cost but also downtime cost. The threshold sR_o is approaching eR_o when the structural dependence impact is small and can be neglected.

The structural dependence-based opportunistic decision is a [major](#) novelty of this work because it allows considering the benefit of structural dependence between components into the maintenance decision-making.

Fig. 7(b) illustrates the multi-level opportunistic maintenance policy for a 4-components system for which the system's directed graph is shown in Fig. 7(a). Suppose that at inspection epoch T_z , 4 components are still working. Their degradation levels are measured and their reliability at the next inspection epoch, T_{z+1} , are predicted as shown in Fig. 7(b). In this case, component 3 is selected for preventive maintenance at T_z because its predicted reliability is below the preventive maintenance threshold R_p . The preventive maintenance on component 3 offers an opportunity to maintain other components to take into account the economic and structural dependence between components. Indeed, the predicted reliability of component 1 is below eR_o , therefore, component 1 is selected for opportunistic maintenance due to the economic dependence (saving setup cost). The directed graph implies that maintenance of component 3 requires disassembly of component 2. Furthermore, the predicted reliability of component 2 is below sR_o , therefore, component 2 is also opportunistically maintained (saving setup cost and downtime cost). The reliability of component 4 is also below the sR_o , but component 4 is not selected for opportunistic maintenance because it is not disassembled.

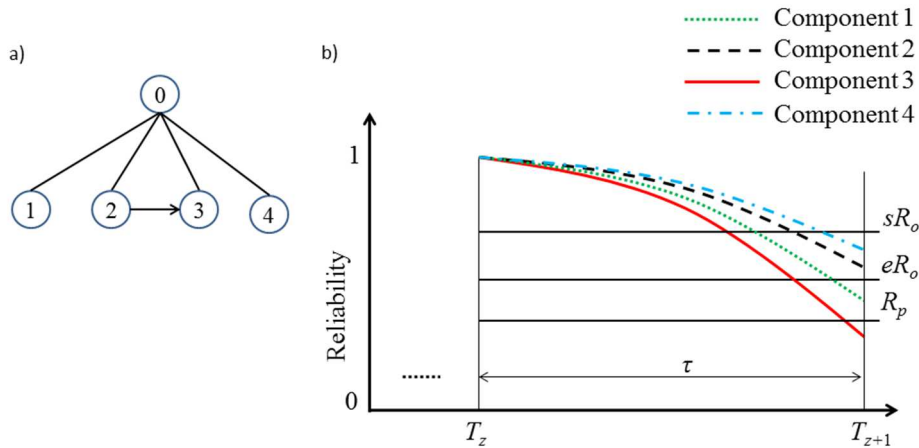


Fig. 7. (a)- Directed graph of a 4-component system and (b)-illustration of the proposed opportunistic maintenance policy

To study the impact of structural dependence in maintenance decision-making, a special case of the proposed multi-level opportunistic maintenance policy is considered by setting $sR_o = eR_o = R_o$. This proposed policy (τ, R_p, eR_o, sR_o) becomes a single level opportunistic policy, which is hereafter denoted as policy (τ, R_p, R_o) . In fact, policy (τ, R_p, R_o) is likely similar to a conventional single level opportunistic policy, see for instance [20, 23]. However, it is important to note that this existing single level opportunistic policy has been introduced to multi-components system to consider only economic dependence between components without considering structural dependence. It needs therefore to be extended to consider the structural dependence in a single opportunistic threshold R_o . A short description of policy (τ, R_p, R_o) is presented in appendix A.

To highlight the effects of structural dependence, a comparison of the proposed policy (τ, R_p, eR_o, sR_o) with policy (τ, R_p, R_o) through a case study is investigated in Section 4.3. Several sensitivity analyses are also conducted in Section 4.4.

3.3. Optimization of the proposed maintenance policy

3.3.1. Maintenance cost model

As mentioned above, the maintenance model consists of four decision variables, including inspection interval, τ , preventive maintenance threshold, R_p , and the two opportunistic maintenance threshold, eR_o and sR_o , respectively. To find an optimal maintenance plan, these decision variables need to be optimized. In the maintenance optimization framework, maintenance cost rate is usually used as the main criterion [7, 14]. Therefore, the long run maintenance cost rate is used as the objective function for maintenance optimization in this study.

The long run maintenance cost rate is defined as [38]:

$$C_\infty(\tau, R_p, eR_o, sR_o) = \lim_{t \rightarrow \infty} \frac{C^t(\tau, R_p, eR_o, sR_o)}{t - t_{down}} \quad (18)$$

Where, $C_t(\tau, R_p, eR_o, sR_o)$ and t_{down} are cumulative maintenance cost and downtime of the system within the period $(0, t]$, respectively. Without losses of generality, it is assumed that $t = N \cdot \tau$ with N is the number of inspections within the period $(0, t]$. The cumulative maintenance cost can be then expressed as follows:

$$C^t(\tau, R_p, eR_o, sR_o) = \mathbb{E}[\sum_{z=1}^N (C_{insp}^z + C_{G^z} + C_{lost}^z)] \quad (19)$$

Where,

- c_{insp}^z is the inspection cost at the z^{th} inspection;
- C_{G^z} is the maintenance cost of group of components G^z which are jointly maintained at the z^{th} inspection;
- $t_{down} = \sum_{z=1}^N \tau_{G^z}$
- $C_{lost}^z = (\tau - \max(T_z - T_i^f)) \cdot c^{lost}$, with T_i^f is the failure time of component i .

It is important to note that a closed-form expression for the maintenance cost rate in Eq. (19) is very difficult or even impossible to obtain due to the complexity of the proposed maintenance policy. An efficient method based on semi-regenerative processes theory is introduced to obtain a closed-form expression for the maintenance cost rate [24]. However, this analytical method is applicable for single-unit deteriorating systems with time-homogeneous degradation behavior. Therefore, in this work, the maintenance cost rate is calculated, given τ, R_p, eR_o, sR_o , by using Monte Carlo simulation. The optimal value of decision variables can be obtained by minimizing the long run maintenance cost rate, i.e.,

$$C_\infty^*(\tau^*, R_p^*, eR_o^*, sR_o^*) = \min_{(\tau, R_p, eR_o, sR_o)} C_\infty(\tau, R_p, eR_o, sR_o), (\tau > 0, 0 < R_p < 1, R_p \leq eR_o < 1, eR_o \leq sR_o < 1) \quad (21)$$

Where, $\tau^*, R_p^*, eR_o^*, sR_o^*$ are the optimal values of inspection interval, preventive, economic and structural dependence based opportunistic maintenance threshold, respectively.

3.3.2. Implementation of PSO algorithm for maintenance optimization

To find the optimal values of decision variables $(\tau^*, R_p^*, eR_o^*, sR_o^*)$, PSO is applied [41-43]. The objective of PSO is to minimize the maintenance cost rate $C_\infty(\tau, R_p, eR_o, sR_o)$ as shown in Eq. (19), subjected to the constraints of $(\tau > 0)$, R_p ($0 < R_p < 1$), eR_o ($R_p \leq eR_o < 1$), and sR_o , ($eR_o \leq sR_o < 1$). The parameters of PSO consist of population size (N_p), maximum number of iterations ($MaxIteration$), and initial weight parameters that control the effect of previous values of particle's velocity and position, ω, c_1, c_2 , respectively. Whereas, ω , is called inertia weight, controls the influence of previous moving velocity of the particle; c_1 , is called as cognitive learning factor, controls the influence of the current position of the particle; and c_2 , is called as social learning factor, controls the influence of current global optimal position of the swarm on searching process. The implementation of PSO is divided by 5 main steps:

- *Step 1- Swarm initialization:* This step generates a swarm with N_p particles and initially generates the position of each particle. The position of particle i , denoted as $Y^{(i)}$, characterized by the value of the decision variables τ, R_p, eR_o, sR_o , subjected to the constraints of $(\tau > 0)$, R_p ($0 < R_p < 1$), eR_o ($R_p \leq eR_o < 1$), and sR_o , ($eR_o \leq sR_o < 1$), i.e., $Y^{(i)} = (\tau^{(i)}, R_p^{(i)}, eR_o^{(i)}, sR_o^{(i)})$.
- *Step 2- Particle fitness evaluation:* For the k^{th} iteration, the long run maintenance cost rate is evaluated according to the value of its position, $C_\infty(\tau^{(i,k)}, R_p^{(i,k)}, eR_o^{(i,k)}, sR_o^{(i,k)})$, by using Eq. (19).
- *Step 3- Update the optimal position of each particle:* For the k^{th} iteration, the optimal position of particle i , denoted as P^i , is updated:
If $C_\infty(\tau^{(i,k)}, R_p^{(i,k)}, eR_o^{(i,k)}, sR_o^{(i,k)}) < C_\infty(\tau^{(i,*)}, R_p^{(i,*)}, eR_o^{(i,*)}, sR_o^{(i,*)})$, then $P^{(i)} = Y_k^{(i)}$, where, $Y_k^{(i)} = (\tau^{(i,k)}, R_p^{(i,k)}, eR_o^{(i,k)}, sR_o^{(i,k)})$ is the position of particle i at the k^{th} iteration.
- *Step 4- Calculate the optimal position of the swarm:* Suppose that at the k^{th} iteration, particle i has the smallest maintenance cost rate in the swarm, so the optimal position of the swarm, denoted as P^g , is updated as follow:
If $C_\infty(\tau^{i,k}, R_p^{i,k}, eR_o^{i,k}, sR_o^{i,k}) < C_\infty(\tau^*, R_p^*, eR_o^*, sR_o^*)$ then, $P^g = Y_k^{(i)}$.
- *Step 5- Update the velocity and position of each particle:* For the k^{th} iteration, the velocity and position of particle i is updated considering its current velocity and position, its optimal position and the swarm optimal position according to Eq. (22) and Eq. (23).

$$v_{k+1}^{(i)} = \omega \cdot v_k^{(i)} + c_1 \cdot rand. (P^{(i)} - Y_k^{(i)}) + c_2 \cdot rand. (P^g - Y_k^{(i)}) \quad (22)$$

$$Y_{k+1}^{(i)} = Y_k^{(i)} + v_{k+1}^{(i)} \quad (23)$$

After finishing the iteration process, the optimal decision parameters are the optimal position of the swarm.

The implementation process of PSO algorithm for optimization of the proposed opportunistic maintenance policy is illustrated in Fig. 8.

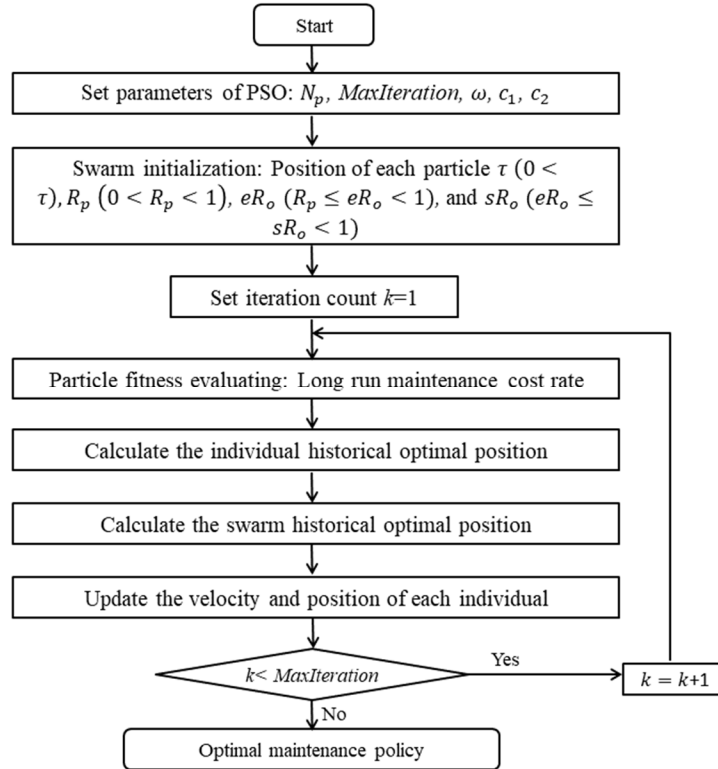


Fig. 8. Implementation of PSO algorithm for the proposed opportunistic maintenance policy

4. Numerical example

This section is devoted to illustrating the use and advantages of the proposed opportunistic maintenance policy for maintenance optimization of an industrial system. In that way, a conveyor system is chosen as show in Fig.2. The chosen conveyor system is composed of 15 interdependent components such as belt, drive motor, couplers, pulleys, bearings. Conveyor system is a durable and reliable equipment in transporting bulk materials. It is widely used in several industries, such as food production, automotive manufacturing, mining, packaging, etc. Maintenance cost accounts for a significant proportion in overall operations cost of the conveyor system, especially for the conveyor used for handling the abrasive materials. The focus of this study is to propose a new maintenance policy to search for the optimal maintenance plan for the conveyor system with minimum maintenance cost.

4.1. Conveyor's parameters

To perform a corrective or preventive maintenance on a component, other components may need to be disassembled as defined by the directed graph (see Fig. 3) and disassembly matrix (see Fig. 4). The degradation and maintenance cost parameters of the system's components are randomly generated by respecting the parameters specification, and the obtained values are given in Table 1. It should be noticed that these parameters can be estimated/extracted from historical maintenance records of the system [25]. However, in our work as no real dataset is available and estimating these data is out of scope, it is considered that these parameters are known in advance. Noting that lifetime of the components is in day

unit while replacement and disassembly durations are in hour unit, cost parameters are in arbitrary cost unit (acu).

Table 1. Data of a conveyor system

Component	Parameters $\alpha_i(days)$	β_i	L_i	τ^r (hour)	τ^d (hour)	c^s	c^p	c^c	c^{insp}	c^d	c^{lost}	H_i	
												μ_{Hi}	σ_{Hi}
1. Belt	1.45	0.42	45	0.15	0.4	150	30	75	50	100	20	1	0.2
2. Drive motor	0.3	0.2	60	0.3	1.0		300	750				1	0.2
3. Coupler 1	0.6	0.4	60	0.2	0.8		50	125				3.2	0.4
4. Coupler 2	0.7	0.5	60	0.2	0.8		55	130				3.2	0.4
5. Head pulley	0.4	0.2	45	0.3	1.0		250	750				0.8	0.1
6. Head bearings	0.5	0.4	45	0.2	0.4		40	100				3.1	0.3
7. Tail pulley	0.4	0.2	45	0.3	1.0		250	750				0.8	0.1
8. Tail bearings	0.5	0.3	45	0.2	0.4		40	100				3.1	0.3
9. Gearbox bearing 1	0.8	0.3	60	0.2	0.4		35	80				3.1	0.3
10. Shaft 1	0.4	0.4	60	0.3	1.0		100	250				1	0.2
11. Gear 1	0.4	0.3	60	0.3	1.0		120	300				1.1	0.2
12. Shaft 2	0.3	0.2	60	0.3	1.0		120	300				1	0.2
13. Gear 2	0.4	0.2	60	0.3	1.0		150	400				1	0.2
14. Gearbox bearing 2	0.6	0.3	60	0.2	0.4		35	80				3.1	0.3
15. Gearbox housing	0.2	0.1	60	0.4	1.2		100	250				0.8	0.2

4.2. Optimal maintenance policy

To find the optimal maintenance policy, the long-run maintenance cost rate is evaluated with different values of the decision variables (τ, R_p, eR_o, sR_o) by stochastic Monte Carlo simulation. PSO algorithm is then applied to find the optimal values of these decision variables.

To ensure the convergence of the long-run maintenance cost rate, the simulation must be done with a very long period. Figure 9 including 20 curves illustrates the convergence of the long-run maintenance cost rate with respect to the number of inspection intervals. The result shows that the convergence reaches from 1.2×10^4 inspection intervals.

For PSO implementation, as recommended in several studies [40-43], the population size is chosen as 50, the initial weight parameters that control the effect of previous values of particle's velocity and position are $\omega = 0.99, c_1 = 2, c_2 = 2$, respectively.

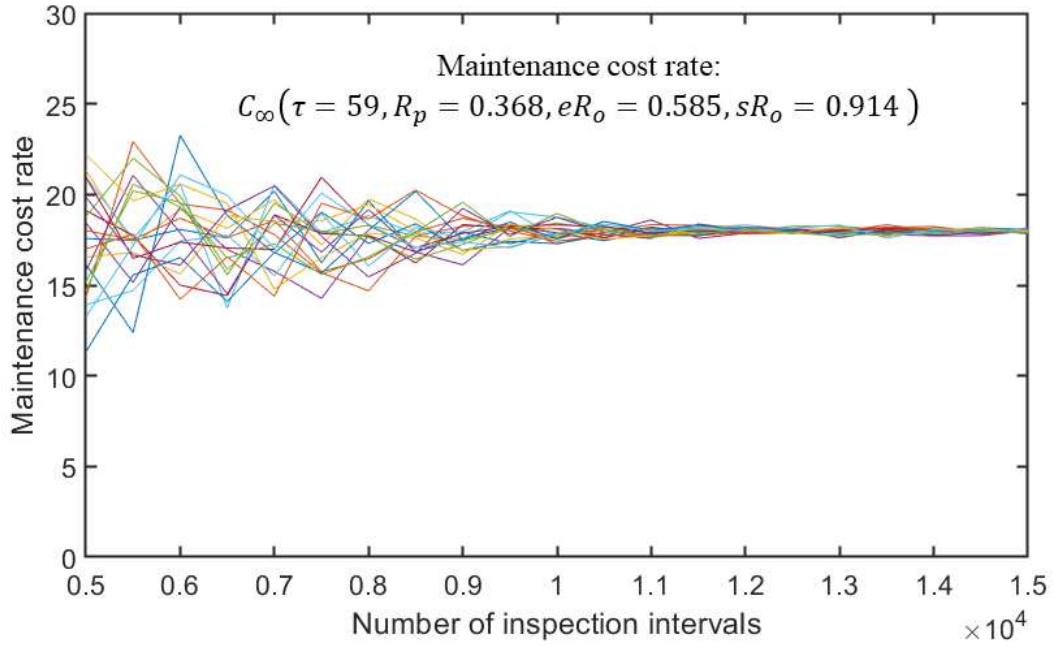


Fig.9 Illustration of the convergence of the long-run maintenance cost rate

By applying the optimization process presented in section 3.3.2, the optimal maintenance policy is obtained with a minimum maintenance cost rate $C_\infty^*(\tau^*, R_p^*, eR_o^*, sR_o^*) = 17.94$ (acu) at $\tau^* = 59, R_p^* = 0.368, eR_o^* = 0.585$ and $sR_o^* = 0.914$. The convergence of PSO algorithm with respected to the number of iterations is illustrated in Fig. 10 (a). It is shown that the convergence is searched from 60 iterations.

Fig. 10 (b) shows the maintenance cost as a function of inspection interval, τ , when $R_p^* = 0.368, eR_o^* = 0.585$ and $sR_o^* = 0.914$. The obtained result shows that the maintenance cost rate is a convex function of the inspection interval and reaches the minimum value at $\tau = 59$ (days). This can be explained by the fact that the shorter inspection interval could reduce the corrective maintenance cost as the components are inspected more frequently. However, it will increase the total inspection cost. On the other hand, increasing the length of inspection interval results in an increase of likelihood of failure of the components between the two consecutive inspection epochs, so the corrective maintenance cost is much more expensive than the preventive maintenance cost.

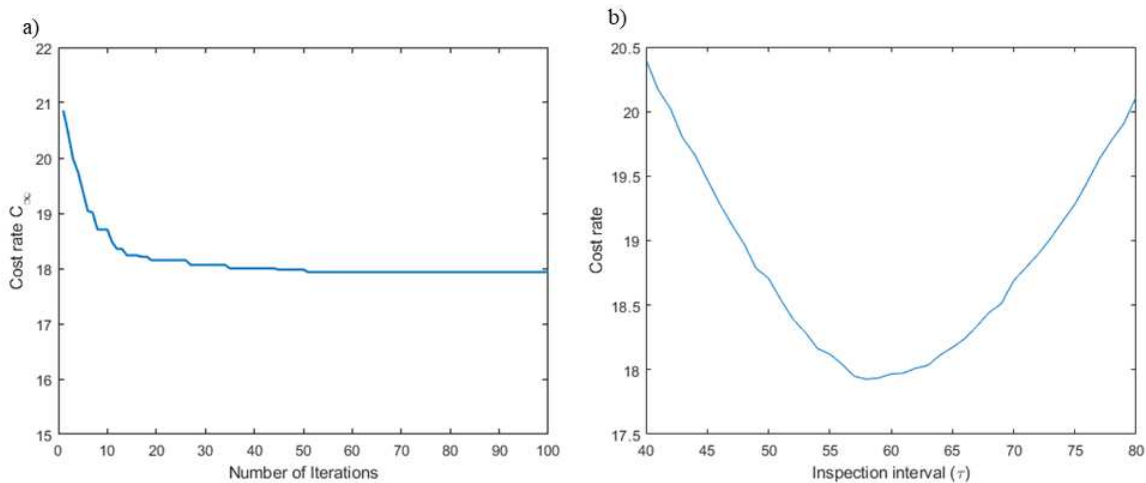


Fig. 10 (a)-Convergence of PSO and (b)-Maintenance cost rate as a function of τ when $R_p^* = 0.368, eR_o^* = 0.585$ and $sR_o^* = 0.915$

4.3. Maintenance strategy comparison

To evaluate the advantages of the proposed multi-level opportunistic maintenance policy, denoted as policy (τ, R_p, eR_o, sR_o) , a performance comparison between the proposed policy and policy (τ, R_p, R_o) , whereby only one level of opportunistic maintenance threshold R_o is applied for all components, is investigated. It must be noticed that the impacts of both economic and structural dependence are considered in the maintenance decision optimization process in the two mentioned above maintenance policies.

The relative excess-cost is used as criterion for performance comparison between the two maintenance policies, which is defined as follows:

$$P_{(\tau, R_p, eR_o, sR_o)/(\tau, R_p, R_o)} = \frac{C_{\infty}^*(\tau^*, R_p^*, R_o^*) - C_{\infty}^*(\tau^*, R_p^*, eR_o^*, sR_o^*)}{C_{\infty}^*(\tau^*, R_p^*, R_o^*)} \cdot 100\% \quad (24)$$

Where $C_{\infty}^*(\tau^*, R_p^*, R_o^*)$ are the minimum maintenance cost rate of policy (τ, R_p, R_o) . From Eq. (24), the two following cases are specified:

- If $P_{(\tau, R_p, eR_o, sR_o)/(\tau, R_p, R_o)} > 0$, the proposed policy is more profitable than policy (τ, R_p, R_o) in terms of maintenance cost rate. The higher $P_{(\tau, R_p, eR_o, sR_o)/(\tau, R_p, R_o)}$, the more the proposed maintenance policy is cost-effective;
- If $P_{(\tau, R_p, eR_o, sR_o)/(\tau, R_p, R_o)} = 0$, both the policies are equally profitable. Note that the case $P_{(\tau, R_p, eR_o, sR_o)/(\tau, R_p, R_o)} < 0$ does not exist because policy (τ, R_p, R_o) is a special case of the proposed policy when $eR_o = sR_o$.

By applying the same optimization process above to the policy (τ, R_p, R_o) , the minimum maintenance cost rate is $C_{\infty}^*(\tau^*, R_p^*, R_o^*) = 18.92$ with optimum values for decision variables $\tau^* = 59, R_p^* = 0.33, R_o^* = 0.692$. When compared to the proposed maintenance policy, the maintenance cost rate of the policy (τ, R_p, R_o) is higher about 4.8%. Fig. 11 shows the maintenance cost rate of the two maintenance policies as a function of inspection interval when the other parameters are as their optimal values.

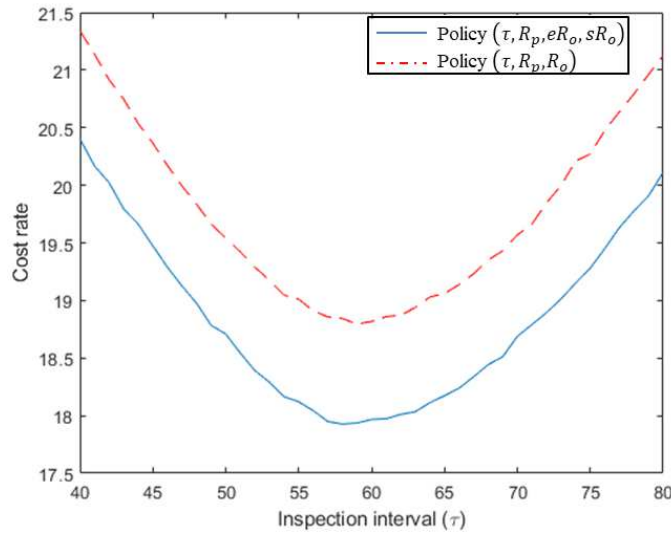


Fig. 11. Maintenance cost rate of the two maintenance policies as a function of inspection interval

Figure 11 underlines that the maintenance cost of the proposed maintenance policy is always lower than that of policy (τ, R_p, R_o) . Policy (τ, R_p, R_o) equally considers all components for opportunistic maintenance without considering the dependences. However, the benefit of opportunistic maintenance on

the disassembled and non-disassembled components are different. Means while, in the proposed policy, it is considering components for opportunistic maintenance based on their dependences with the maintained components. Therefore, the proposed policy can exploit the highest benefit of opportunistic maintenance. Of course, the policy (τ, R_p, R_o) is simpler than the proposed maintenance policy since it requires only three decision variables (τ, R_p, R_o) while four decision variables (τ, R_p, eR_o, sR_o) are needed for the proposed policy.

4.4. Sensitivity analyses

The result in section 4.3 shows that the proposed multi-level opportunistic maintenance policy is significantly more cost-effective than conventional opportunistic maintenance policy (τ, R_p, R_o) . However, the result is obtained with given values of system parameters. To study the impacts of economic and/or structural dependence in maintenance cost rate in a more general way, several sensitivity analyses to dependence degree need to be investigated. In that way, three sensitivity analyses are carried out in this section.

4.4.1. Sensitivity analysis to the disassembly duration

A sensitivity analysis is numerically conducted to understand how the preventive opportunistic maintenance thresholds and the relative cost-benefit (calculated by Eq. (24)) change when varying the disassembly duration. Fig.12 (a) shows the optimum maintenance thresholds of the two policies as a function of the disassembly duration knowing that the disassembly duration of all components is varied from 100% (the current values shown in Table 1) to 0%. Note that the discrete line represents the maintenance thresholds of policy (τ, R_p, R_o) , while continuous line represents the maintenance thresholds of the proposed opportunistic policy. R_{p1} and R_{p2} denote the preventive maintenance threshold of two policies (τ, R_p, eR_o, sR_o) and (τ, R_p, R_o) respectively; R_{o2} denotes the opportunistic maintenance threshold of policy (τ, R_p, R_o) .

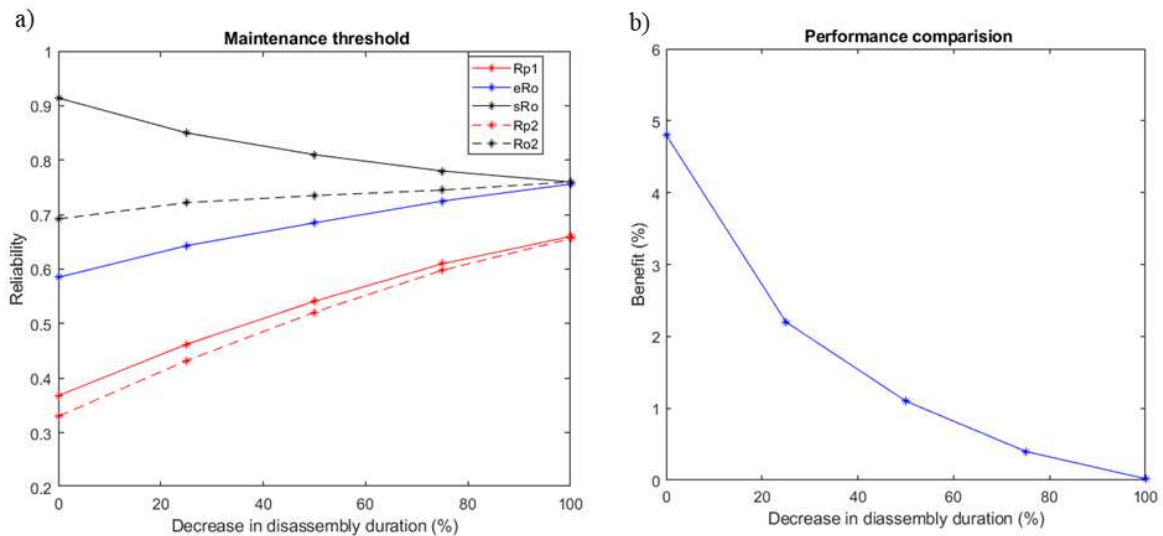


Fig. 12. (a)-Optimal maintenance thresholds and (b)-performance comparison between the two maintenance policies as a function of the degree of disassembly duration

The obtained results show that the gap between eR_o and sR_o becomes small when the structural dependence between components is decreasing, and finally, converges to the opportunistic maintenance threshold of the policy (τ, R_p, R_o) when the disassembly duration is going to zero. Fig. 1 (b) shows that the advantage of the proposed opportunistic policy (relative excess-cost) decreases when the disassembly duration decreases. When the disassembly duration is equal to zero, the proposed opportunistic policy becomes policy (τ, R_p, R_o) . It is noticeable that when the decreasing in disassembly duration is approaching 100%, i.e., the disassembly duration is zero, the preventive maintenance threshold (R_p) of both policies increases significantly. This can be explained by the fact that the preventive maintenance threshold depends on the ratio between the PM cost and CM cost (C_i^p/C_i^c). Note that if C_i^p/C_i^c is small, i.e., $C_i^c \gg C_i^p$, then R_p is high to promote PM maintenance more frequently. Indeed, it is shown in Eq.(3), Eq. (4), and Eq. (5) that when the disassembly duration decreases to zero, C_i^p/C_i^c significantly decreases.

4.4.2. Sensitivity analysis to maintenance setup cost

5. In addition to analyze the contribution of economic dependence, it is necessary to analyze how economic dependence effects on the maintenance decision variables and the performance comparison between components. As mentioned in Section 2.2, the economic dependence between components is represented by the setup cost. In that way, to investigate the sensitivity to the economic dependence, the maintenance setup cost is varied from 100% (the setup cost in Table 1) to 0%. The obtained results are shown in Fig.13.

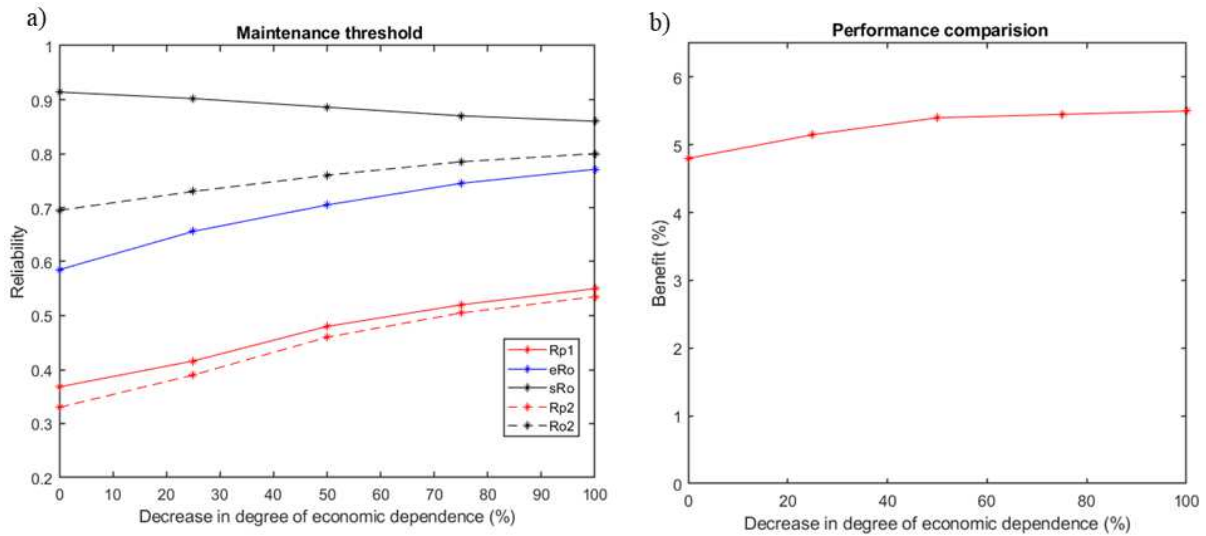


Fig. 13 (a)-Optimal maintenance thresholds and (b)-performance comparison between the two maintenance policies as a function of the degree of economic dependence

Figure 13 (a) shows that the policy (τ, R_p, eR_o, sR_o) is not converse to policy (τ, R_p, R_o) even the economic dependence is totally released (setup cost is zeros). Figure 13 (b) shows that the relative cost-benefit is slightly increasing when reducing the degree of economic dependence, i.e., the proposed opportunistic maintenance is better than policy (τ, R_p, R_o) . This is because the benefits of the policy (τ, R_p, R_o) mainly comes from the economic dependence, while the policy (τ, R_p, eR_o, sR_o) comes from

both economic and structural dependences. Therefore, when the degree of economic dependence decreases, the benefit of the policy (τ, R_p, R_o) decreases faster than that of the policy (τ, R_p, eR_o, sR_o) .

5.1.1. Sensitivity analysis to joint consideration of economic and structural dependence

The sensitivity analysis on the impact of economic dependence and structural dependences individually on the maintenance thresholds and performance have been conducted in the previous sections. In this section, the degree of both economic and structural dependences are simultaneously varied from 100% (the setup cost and disassembly duration in Table 1) to 0%. Fig. 14 (a) shows the change of the optimum maintenance thresholds regardless to a decreasing of disassembly duration and setup cost on the maintenance thresholds and Fig. 14 (b) sketches the relative excess-cost of the two maintenance policies as a function of the decreasing level of disassembly duration and setup cost. It is shown that when both economic and structural dependences are completely released, all maintenance thresholds converge to the preventive maintenance threshold. This means that both policy (τ, R_p, eR_o, sR_o) and policy (τ, R_p, R_o) become the conventional preventive maintenance without any opportunistic maintenance, i.e., policy (τ, R_p) .

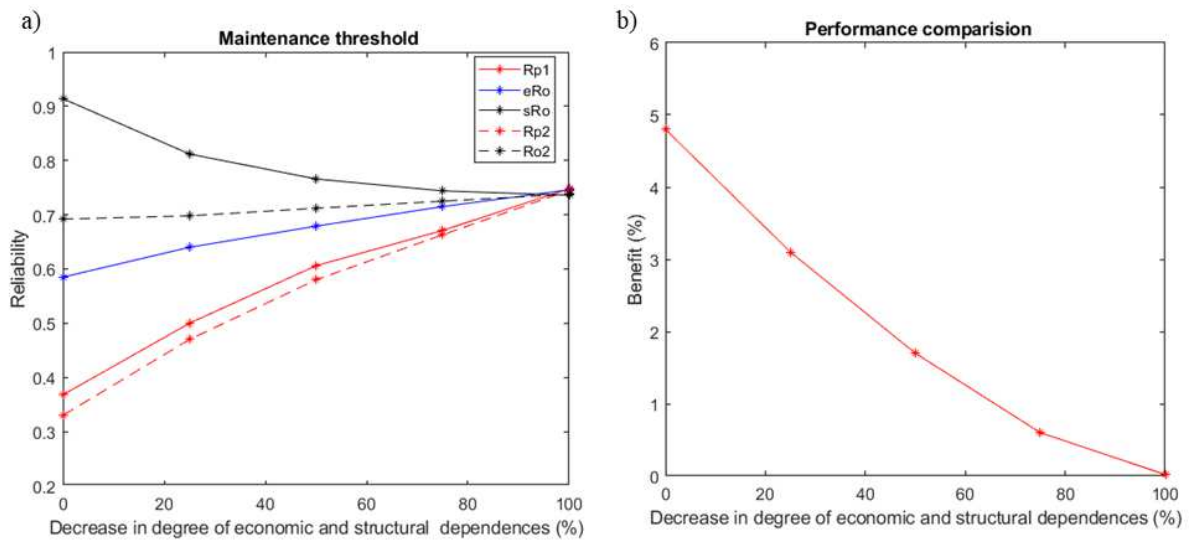


Fig. 14 (a)-Maintenance thresholds and (b)-performance comparison when the degree of economic and structural dependence simultaneously decrease.

6. Conclusions

In this paper, a novel multi-level opportunistic predictive maintenance approach is proposed for multi-component system considering both structural and economic dependences. A degradation model that allows considering impact of disassembly operation is firstly developed. The impact of economic and structural dependence is also formulated. Then, to select one or several components to be maintained, one preventive threshold and two opportunistic thresholds are introduced for preventive and opportunistic maintenance decision-making, respectively. The economic dependence-based opportunistic threshold is applied to the non-disassembled components to promote the economic dependence between components. The structural dependence-based opportunistic threshold is applied to the disassembled components to consider the structural dependence between components. To evaluate the performance of the proposed

opportunistic maintenance approach, a cost model is proposed. Furthermore, PSO algorithm is implemented to find an optimal opportunistic maintenance plan. This implementation helps to significantly reduce the computing time. Numerous numerical experiments are conducted to show the feasibility and the advantages of the proposed maintenance approach. A comparison study with a conventional opportunistic maintenance policy (with only one level of opportunistic maintenance threshold) is also investigated. The obtained results show that the proposed maintenance approach can better exploit the structural dependence between components in opportunistic maintenance with the higher benefit when compared to a conventional opportunistic maintenance approach. In addition, the proposed maintenance policy can turn into a conventional maintenance one when all components are structurally independent.

In this study, the disassembly matrix is established manually. However, for a complex industrial system, e.g., system consisting of hundreds of components, such as aircraft engine, manually establishing the disassembly matrix could face the human errors. In that way, development of a tool to automatically build the disassembly matrix of the system from the CAD (Computer-Aided-Design) model could be considered to improve this work. Another prospect of this work could be to consider the degree of expertise of maintenance technician in allocating maintenance resources for maintenance optimization.

Appendix

Appendix A. Short description of the maintenance policy (τ, R_p, R_o)

For this policy, τ, R_p, R_o are three decision variables. The system's components are inspected regularly at $T_z = z \cdot \tau, (z = 1, 2, \dots)$. The maintenance decision rules at each inspection are as follow:

- *CM decision*: if the component is failed, i.e., its degradation level reach its failure threshold, it is correctively replaced.
- *PM Decision*: if component is surviving, its reliability at the next inspection is evaluated. The component is preventively replaced if its predicted reliability is less than the preventive maintenance threshold, R_p .
- *OM decision*: if there is at least one corrective and/or preventive maintenance action, other components can be opportunistically replaced if their predicted reliability is below the opportunistic maintenance threshold, R_o . To consider both economic and structural dependence between components, the selection process of OM decision is divided into two phases. In phase 1, the OM decision is applied to all surviving components without considering the disassembly impacts on the degradation process of these components. After phase 1, several surviving components may be selected to be opportunistically maintained with maintenance of components selected from CM or PM decision. Maintenance on the selected components may require to disassembly several no-selected components. In phase 2, OM decision is applied again on these disassembled components by integrating the disassembly impacts on their degradation process when evaluating their predicted reliability.

Similarly, as presented in section 3.3.1, the cost model of policy (τ, R_p, R_o) can be formulated as:

$$C_{\infty}(\tau, R_p, R_o) = \frac{\mathbb{E}[\sum_{z=1}^N (C_{insp}^z + C_{G^z} + C_{lost}^z)]}{\mathbb{E}[t_{end} - t_{down}]}$$

The optimal maintenance decision variables of this policy can be obtained by minimizing the long run maintenance cost rate:

$$C_{\infty}^*(\tau^*, R_p^*, R_o^*) = \min_{(\tau, R_p, R_o)} C_{\infty}(\tau, R_p, R_o), (\tau > 0, 0 < R_p < 1, R_p \leq R_o < 1)$$

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