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A dynamic maintenance decision approach based on maintenance action grouping for HVAC maintenance costs savings in Non-residential buildings

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Abstract: Huge maintenance costs in non-residential buildings weighted it down the overall costs allocated to HVAC (Heating, ventilation and air conditioning) system maintenance. Maintenance Management objective is to reduce or even avoid the corrective maintenance by proper planning and implementation of maintenance tasks at the right time. The aim of this paper is to early plan maintenance interventions for a multi-components system based on stoppages characteristics, system RUL (Remaining Useful Life) and components criticalities. This maintenance plan is made through a dynamic maintenance decision approach (DMDA) to help the maintenance expert in taking decision. Since combining maintenance activities is cheaper than performing maintenance on components separately, maintenance actions groupings are performed in the proposed approach by the mean of odds algorithm. This will allow optimizing system availability, reducing maintenance costs and delaying as late as possible maintenance interventions. Components criticalities are used for prioritizing components in the grouping process. Moreover, DMDA take into account predictive information such as system/components RUL, given by an existing prognostic process. At the end, a numerical example of a HVAC system with five components (Heat exchanger, filter, dampers, valve and fan) demonstrates the use and the advantages of the proposed DMDA.

Keywords: maintenance decision making, prognostics, maintenance costs, non-residential buildings, HVAC system, maintenance grouping, odds algorithm, opportunity, stoppage, optimal stopping, availability.

1. INTRODUCTION

The objective of maintenance management is to reduce or even avoid the corrective maintenance by proper planning and implementation of maintenance tasks at the right time (Au-yong et al. 2014). One universal maintenance performance measurement, is maintenance cost. Indeed, a significant amount of the annual operational costs of facilities is attributed to maintenance costs. Maintenance costs are often used to compare maintenance performance between companies or between facilities within the same company. Hence, the challenge is to find an efficient strategy in order to plan maintenance tasks since the system is multi-components. A proactive maintenance decision has to be made based on predictive information such as RUL (Remaining Useful Life) estimate. Remaining Useful life impacts on the planning of maintenance activities, spare parts provision, operational performance and the profitability of the facility owner (Si et al. 2011).

Over the last decades, a particular attention has been paid on grouping maintenance for multi-components facilities. The interest of the maintenance grouping is to take the advantages of positive economic dependence that implies that combining maintenance activities is cheaper than performing maintenance on

components separately (Do et al. 2015). Hence, a proper maintenance actions grouping must rely on strong criteria. In literature, several criteria have been proposed. Authors in (Fitouri et al. 2016), (Vu et al. 2014) proposed a maintenance grouping approach for multi-components facilities based on structural dependencies between those components. (Van Horenbeek & Pintelon 2013) present a method based on the updated failure probability distribution. Interested readers can see the following: (Lin & Wang 2010; Bouvard et al. 2011). In the existing maintenance grouping approaches, maintenance durations are neglected. (Do et al. 2015) propose a maintenance grouping approach using genetic algorithm and MULTIFIT taking into account maintenance durations. Most of the works in literature are focusing on maintenance cost optimization for reducing maintenance costs. Nevertheless, in some application, one may want to optimize the availability of the system and delay as late as possible the maintenance intervention.

This paper proposes a maintenance grouping approach based on the concept of opportunity developed by (Thomas et al. 2008) for production systems. In the present work, the application domain is Heating, ventilation and air conditioning (HVAC) in buildings and especially Non-residential buildings such as

Airport, hostel, commercial and office buildings. HVAC system is responsible of thermal comfort and indoor air quality. Simply, a HVAC system is a set of components that work together to provide conditioned air to an occupied space to maintain the desired comfort level (Sugarman 2005) As depicted on (Fig.1), HVAC system consists of chillers, boilers, hot water pump, piping, pipes, valves, dampers, air handling unit (AHU) (ASHRAE 2012), (Handbook 2009).

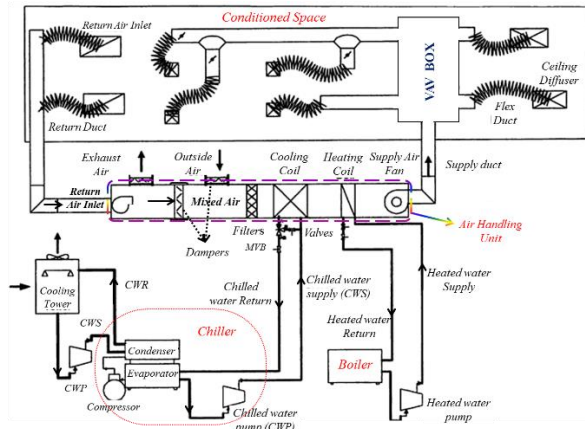


Fig. 1. HVAC system Overview

HVAC maintenance, being a part of building maintenance (BM), is needed to keep HVAC running and prevent any sudden failure that can bring the whole system out of acceptable operating conditions. The reasons to properly maintain the HVAC system include energy savings, decreasing of maintenance costs, prevent hazardous conditions, increase the service lifetime of HVAC equipment and guarantee thermal comfort for building's occupants.

HVAC maintenance like others facilities is based usually on manufacturer's guidelines and specifications. The interest in buildings maintenance is that the building operation is conditioned by the presence of people in building. This means that HVAC system can be also stopped because nobody is present in the building or a part of it (nobody in a room hotel or in an office). Hence, not only planned stoppages for maintenance tasks could be used (replacements, adjustments, major overhauls, inspections and lubrications, adjustment or calibrations, cleaning (Springer & Dakin 2013), but also stoppages out of maintenance (change in building occupancy). All these stoppages are the inputs of the proposed approach. Based on the remaining life of the system, some of stoppages will be selected to perform maintenance actions on HVAC components. In the rest of the paper, these stoppages are called opportunities for maintenance and are defined as the stoppages that start before the end of life of the system. According to the type of buildings, opportunities to perform maintenance on HVAC system are infrequent. In this case, the grouping maintenance philosophy has to be introduced in HVAC maintenance for tactically build

maintenance activities schedule. This will lead to time and maintenance costs savings and HVAC availability optimization as well. A mathematical tool known as "odds algorithm" applied for maintenance objectives in (Thomas et al. 2008), is used in the proposal. Odds algorithm provided a classification of stoppages/opportunities in a decreasing order of relevance for each components.

Hence, this paper aims to develop an opportunity formalism based dynamic maintenance grouping approach for early maintenance planning. It contributes to take dynamic decision in predictive maintenance strategy. Moreover, components criticality and predictive information such as RULs components/system are used in order to give priority to one components within a group. This paper is organized as follows. The proposed DMDA is presented in section 2 wherein every steps will be detailed. Section 3 is devoted to illustrate the use and the advantages of the proposed approach through a numerical example. Finally, section 4 concludes and highlights prospects works.

2. DYNAMIC MAINTENANCE DECISION APPROACH

This section deals with the presentation of the dynamic maintenance grouping process (DMGP) proposed in this paper. The proposed model incorporates the predictive information, components criticality and stoppages characteristics to build the maintenance scheduling for decision taking. Figure 3 depicts the general architecture of the proposed approach.

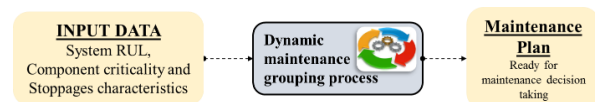


Fig. 2. Dynamic maintenance grouping architecture

2.1. Inputs Data

Three inputs are required for DMGP's use: system RUL, components criticality, date and duration of stoppages.

2.1.1. System RUL

The remaining useful life (RUL) of a system is defined as the length from the current time to the end of the useful life (Fig.3). The RUL of a system is linked to the RUL of its components that are provided by a prognostic process. RUL is a random variable as it is influenced by the stochastic characteristics of the component degradation (Edwards et al. 2010), (Voisin et al. 2010). Indeed, it depends on the current age of the asset or component, the operating environment and the observed condition monitoring (CM) or health information. Thereby, the RUL is given as a probabilistic estimate bounded with confidence intervals (Sankararaman & Goebel 2013). Numerous

methods and tools regarding failure prognostics have been proposed and reported in the literature (Medjaher et al. 2013; An et al. 2013; Wang et al. 2012; Kamran 2014). These methods will be not developed in this paper. A prognostic process is assumed exist and ready to be used.

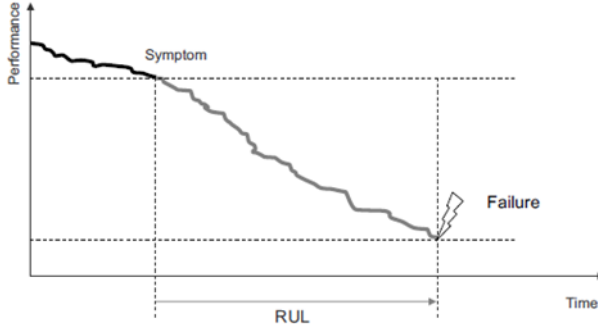


Fig. 3. Remaining Useful Life illustration (Medjaher et al. 2013)

2.1.2. Components Criticality

The criticality of a component means how much the failure mechanism affects the system KPIs (Keys Performance Indicators). The criticality is determined through Failures Modes effects analysis (FMEA) by the product of frequency (FI), severity (SI) and detection (DI) indexes.

$$Crit = FI * SI * DI \quad (1)$$

In this paper, criticality elaboration is not the focus and will not be developed. It is assumed that the criticality already exists. Components criticality will be used in the proposal for the grouping process.

2.1.3. Stoppages characteristics

For an observation horizon, the calendar of available facility stoppages is available. The stoppages include those scheduled for systematic maintenance and those out of maintenance reasons. Depending on the type of building, these stoppages are infrequent.

A stoppage is defined by the couple $(St_i; L_i)_{1 \leq i \leq n}$, respectively the starting time of a stoppage and its length and $i = \{1, 2, \dots, n\}$, the number of system stoppages. A stoppage exists if $L_i > 0$. Then, the dynamic grouping process can be launched.

2.2. Dynamic Grouping Process

This part is the cornerstone of the proposal. It consists of two main sub-processes shown in Fig.4: *To classify opportunities* and *to group components*. More information about these processes are provided hereafter.

2.2.1. To classify opportunities

As stated before, an opportunity is a stoppage which appears (planned or not), before the RUL of the system.

For a multi-components system, one needs to choose them among all the scheduled stoppages. Hence, this choice is based on the RUL estimate well defined earlier.

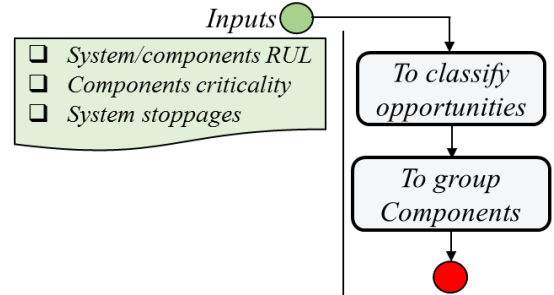


Fig. 4. Architecture of Dynamic grouping process

In figure 5, the probabilistic RUL is represented by a density of probability. It is obvious to see that the first three stoppages can be selected as opportunities without uncertainty. For the last three one, the decision is not so simple. Thus, the issue here can be formulated as follow: Do the last three stoppages could be used to perform maintenance intervention? If so, what is the risk associated with it? One can note that the decision to select a stoppage as an opportunity is associated with a risk, linked to the failure of the system to happen before.

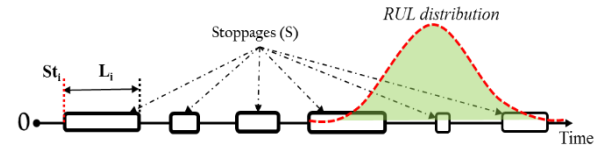


Fig. 5. Stoppages illustration and RUL effects

We define an alpha level corresponding to the decision maker choice. This level allows setting a time, corresponding to the time where the cumulative density function associated with the RUL equals to alpha. The selection of opportunities will be based on this time noted T_{alpha} that represent the failure time of the system (Fig.6).

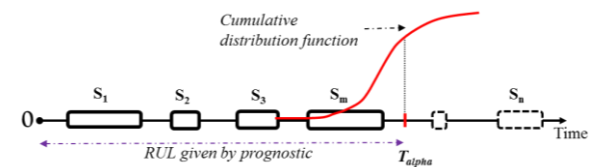


Fig. 6. Opportunities choice with deterministic RUL

Next, the classification of opportunities is made through a tool so-called odds algorithm, based on Bruss theorem (Bruss 2003). The odd theorem gives a unified answer to a class of stopping problems on sequences of independent indicator functions (Bruss 2003). It is the elegance of simplicity, which makes the odds theorem attractive. This theorem was introduced by Thomas (Thomas et al. 2008) in maintenance area to answer the following question: Given a maintenance action, what is the most appropriate opportunity to perform it? In

other words, is it possible to classify opportunities for each component of the system?

Odds algorithm starts with definition of probabilities associated to events' appearance, here related to opportunities. To apply it in maintenance, two characteristics of components, usually available in CMMS (Computerized Maintenance Management System), are used: reliability and maintainability. Reliability is assumed to be a Weibull distribution with the shape parameter β and the scale parameter η . Maintainability is supposed following an exponential law with parameter μ . Thereafter, we call 'success' a stoppage where the system is alive at time St_i and maintainable during L_i with now $i = \{1, 2, \dots, m\}$, m the number of opportunities. The probability to have a success is P_i . This probability of success is computed by the product of reliability and maintainability as follow.

$$P_i = R(St_i) \cdot M(L_i),_{1 \leq i \leq m} \quad (2)$$

Then, the odds are computed through the following equation.

$$r_i = \frac{R(St_i) \cdot M(L_i)}{1 - R(St_i) \cdot M(L_i)} \quad (3)$$

The next step consists in summing up the odds from the last opportunity until reaching the value $s \leq 1$. Then, the first stoppage where the sum of odds will exceed 1 is the optimal one and the next stoppages, called alternatives, are considered as sub-optimal. Then, it is removed from the opportunities list and the sum is recomputed, in order to get the second best success. The same operation has to be reiterated until the sum of odds is less than one. The result is a classification of all opportunities.

Finally, the expert has at his disposal an ordered list of all opportunities ranking according to their pertinence order. This will help maintenance expert to plan a maintenance action in another stoppage if for example spares parts are not available during the first considered stoppage. The odds algorithm provides a reward for each opportunity in the classification. This reward is computed by the following expression:

$$V_s = \left(\prod_{z=s}^m 1 - R(St_z) \cdot M(L_z) \right) \cdot \left(\sum_{z=s}^m \frac{R(St_z) \cdot M(L_z)}{1 - R(St_z) \cdot M(L_z)} \right) \quad (4)$$

Knowing the stoppages parameters, odds algorithm is used to develop the proposal. More details are given in the following section.

The odds algorithm is run for each component of the given system. For each component, an ordered list of opportunities to perform maintenance (Table 1). Then, based on this classification (list), one has to decide for

each stoppage the group of component to be maintained.

Table 1: Opportunities classification

Components	C_1	C_2	...	C_n
Opportunities classification	S_4	S_5	...	S_4
	S_2	S_3	...	S_1
		S_1	...	

One property of the classification for a component is that the sequence of stoppages is always in reverse order. If $S_{q, 1 \leq q \leq m}$ is the first stoppage in the classification for a component, the following stoppages are S_{q-1}, S_{q-2}, \dots . For example in table 1, we have the sequence S_5, S_3 and S_3 . It means that considering a success for a component, the next success in the sequence is always earlier. Let note CS a matrix such that

$$\begin{cases} CS_{i,j} = 1, \text{ if } S_j \text{ is a succes for } C_i \\ CS_{i,j} = 0, \text{ Otherwise} \end{cases}$$

This matrix is useful in grouping process.

2.2.2. To group components

The grouping criterion is the optimal stoppage.

For each stoppage, components with the same optimal stoppage are considered. Therefore, let G be set of sets such that $G = \{G_1, \dots, G_k\}_{1 \leq k \leq p}$, with p the number of groups. p is less or equal to m , the number of opportunities, since some stoppages may not be optimal for any component. G_k is a subset defined as follow:

$$G_k = \left\{ C_i / \max(cs_{i,j}=1)=k \right\} \quad (5)$$

The grouping process starts with the greater stoppage in the classification. The sum of the Mean Time to Repair (MTTR) of components is computed for each group as follow.

$$Sum_{G_k} = \sum_{i=1}^{cn_k} MTTR_i \quad (6)$$

This sum has to be less or equal to the length of stoppage. cn_k is the number of components in G_k .

$$Sum_{G_k} \leq L_k \quad (7)$$

If (7) is satisfied, the whole component can be maintained during S_k . If the condition (7) is not satisfied, some maintenance action will not be performed during S_k , meaning some components have to be removed from G_k , such that (7) is satisfied. The maintenance action to be shift has to be performed earlier according to the ordered list obtained at stage 1 (table 1). As we aim to maximize the usage of all

components, the shift has to be minimized. Hence, we will consider as shifting candidate the component according to their next-suboptimal stoppages.

Now let order the components according to the possibility to shift them: the first rank corresponds to the first candidate to shift. The ordering criteria are:

a) The stoppage shift, noted l_{C_i} . It represents the number of component shifting from a stoppage to the next where $cs_{i,j} = 1$. The shifting has to be minimized since one looking in maintenance the longest usage.

$$\min\{l_{C_i, 1 \leq i \leq cn_k} / cs_{i,k} = 1\} \quad (8)$$

The smallest the stoppage shift, the better candidate is the component.

b) The criticality of the component $Crit(C_j)$ is classified in decreasing order. The higher the criticality, the better candidate is the component.

c) The RUL of the component C_j is $RUL(C_j)$. Since we aim to optimize the usage of the components, the RULs are classified in decreasing order. The higher the RUL, the better candidate is the component.

The output of the dynamic maintenance decision approach is the maintenance action planning in a tactical level.

3. NUMERICAL EXAMPLE

An example is given to validate the proposed dynamic maintenance decision approach. A study is performed on AHU (Air Handling Unit) system with five components: Heat exchanger, filter, valve, fan and damper. We assume that only one maintenance action has to be performed on each component. Their lengths (LMA) are given in table 1. The priority order is determined through components criticalities. Knowing that KPI (Key Performance Indicator) is energy efficiency, Heat exchanger (C_1) is more critical than other component. It is follow by filter (C_2), valve (C_3), fan (C_4) and damper (C_5). For each component, reliability follows a Weibull law with scale parameter β , shape parameter η (Table 1). Maintainability follows an exponential distribution with $\mu = 1/LMA$. It is assumed that prognostic process gave a RUL from which eighteen stoppages of AHU system have been selected.

Table 2: Components and their characteristics

Components	C_1	C_2	C_3	C_4	C_5
β	6	1	3	2.5	2
η	800	400	500	700	600
MTTR	5	3	1	2	4
Criticality	100	50	75	90	110

Stoppages characteristics are like following:

Starting Time : [150; 300; 350; 400; 450; 557; 652; 700; 850; 951; 1050; 1141; 1228; 1322; 1410; 1508; 1612; 1706; 1803; 1904]

Stoppages length:

[1; 5; 9; 2; 6; 5; 4; 6; 7; 7; 8; 9; 9; 1; 14; 4; 1; 6; 10; 7].

The table shows the results of odds algorithm for the aforementioned stoppages and components characteristics.

Table 3: Odds Results

Comp onents	Stoppages/opportunities classification						
	S_8	S_6	S_5	S_4	S_3	S_2	
C_1	S_8	S_6	S_5	S_4	S_3	S_2	
C_2	S_6	S_5	S_3	S_2			
C_3	S_5	S_4	S_3	S_2	S_1		
C_4	S_8	S_7	S_6	S_5	S_4	S_3	S_2
C_5	S_6	S_5	S_3	S_2			

In table 3, the optimal stoppage preconize by the odds algorithm is optimal for the considered component. The following stoppages are alternatives considered as sub-optimal and are helpful to maintenance expert as stated earlier. The table 4 represents the matrix CS . The red arrows show the number of shifting for each component.

Table 4: Matrix

Stoppage	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
C_1	0	1	1	1	1	1	0	1
C_2	0	1	1	0	1	1	0	0
C_3	0	1	1	1	1	0	0	0
C_4	0	1	1	1	1	1	1	1
C_5	0	1	1	0	1	1	0	0

The greater stoppage in the classification (Table 3) is S_8 . Hence, the grouping process is like follow:

➤ $G_8 = \{C_1, C_4\}$ with stoppage S_8

$$Sum_{G_8} = MTTR_{C_1} + MTTR_{C_4} = 5 + 2 = 7h$$

$Sum_{G_8} > L_{S_8} = 6h$, Condition (7) is not satisfied.

Then, $\min(l_{C_1} = 2, l_{C_4} = 1) = l_{C_4}$ That means C_4 is removed from G_8 and C_1 will stay.

$$G_8 = \{C_1\} \text{ and } G_7 = \emptyset \cup \{C_4\}$$

➤ $G_7 = \{C_4\}$, with stoppage S_7

$Sum_{G_7} = MTTR_{C_4} = 2h < L_{S_7} = 4h$; Condition (7) is satisfied.

➤ $G_6 = \{C_2, C_5\}$ with stoppage S_6

$$Sum_{G_6} = MTTR_{C_2} + MTTR_{C_5} = 3 + 4 = 7h$$

$Sum_{G_6} > L_{S_6} = 5h$, Condition (7) is not satisfied

Then, $\min(l_{C_2} = 1, l_{C_5} = 1) = \emptyset$. That means the next criterion that is criticality will be used.

$$Crit(C_2) = 50 \text{ and } Crit(C_5) = 110$$

C_5 is removed from G_6 and C_2 will stay.

$$G_6 = \{C_2\} \text{ and } G_4 = \{C_3\} \cup \{C_5\}$$

➤ $G_5 = \{C_3, C_5\}$ with stoppage S_5

$$Sum_{G_5} = MTTR_{C_3} + MTTR_{C_5} = 1 + 4 = 5h$$

$Sum_{G_5} < L_{S_5} = 6h$, Condition (7) is satisfied

Finally, the grouping process gives the following results shown in table 3.

Table 5: Grouping process results

Group	G_1	G_2	G_3	G_4
	$\{C_1\}$	$\{C_2\}$	$\{C_3, C_5\}$	$\{C_4\}$
Sum	$5h$	$3h$	$5h$	$2h$
Stoppage	S_8	S_6	S_5	S_7
Length S	$6h$	$5h$	$6h$	$4h$

Now, the maintenance expert has at his disposal grouping process results. He is able to take decision with more confidence.

4. CONCLUSION

In this paper, a dynamic maintenance grouping approach is proposed to build a maintenance schedule for a multi-components system. The grouping criterion is the optimal stoppage provide by the mathematical tool so called odds algorithm. Hence, this contribution is original. Moreover, Criticality as well as prediction information such as system RUL are used. Indeed, the proposed approach is proved dynamic because of three aspects: 1- If the condition (7) is not satisfied, some components are reallocated to another group based on three criteria given above; 2- Any time, RUL of the system is recomputed and the maintenance expert can change the level alpha. The DMDA leads to optimize the availability of the system and delay as late as possible the maintenance intervention

Our future work will be to applied the proposed approach in real system to prove its efficiency and compared its performance to several conventional maintenance policies. Moreover, the RUL uncertainties, spares parts and human resource will be considered in DMDA. The authors would like to acknowledge the financial support of the European Commission under the Seventh Framework Program titled Energy-In-Time that aims to develop Smart Energy Simulation Based Control method to reduce the

energy consumption and energy bill in the operational stage of existing non-residential buildings. (<https://www.energyintime.eu/>).

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