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*I dedicate this work to all the people, family and friends,
who have been by my side during my school and university life.*

Abstract

In general, the maintenance of system equipment in the industrial field is necessary to avoid breakdowns, as the system may deteriorate due to the operating and environmental conditions. However, most of the maintenance strategies adopted in industry are essentially based on theoretical models that do not take into account the real conditions.

This report presents the work we achieved during our graduation internship at LGIPM Lab at Lorraine University. We developed a selective predictive maintenance model for a multi-parallel series system where the objective was determining an optimal sequence of maintenance actions that provides the desired level of system reliability for each mission. The selecting of components to be maintained is based on the their actual age determined by the prediction model according to real data maintenance.

Assuming that system reliability is exponential depending on its real age and each maintenance policy is characterized by its ability to improve the actual age of system components, an optimization model based on the EGA algorithm uses the predictions obtained as input data to identify the best maintenance policy for each component taking into account the constrained maintenance resources. Finally, the numerical results of the proposed idea applied on the FMS data are presented to show the robustness of the model.

Keywords: Selective Maintenance; Clustering algorithm; Artificial Neural Network; Machine Learning Algorithms; Multi-level maintenance; Reliability; Meta-heuristic Algorithm; Optimization.

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Acronyms

SM Selective Maintenance

Pd.M Predictive Maintenance

CM Corrective Maintenance

PM Preventive Maintenance

ABAO As Bad As Old

AGAN As Good As New

EGD Extended Great Deluge

AI Artificial Intelligence

ML Machine Learning

ANN Artificial Neural Network

SVR Support Vector Regression

MAE Mean Absolute Error

MSE Mean Squared Error

MAPE Mean Absolute Percentage Error

BP Back Propagation

RUL Remaining Useful life

FMS Flexible Manufacturing System

MTBF Mean Time Between Failure

Nb.PM Number of Preventive Maintenance

Nb.CM Number of Corrective Maintenance

Introduction

In industry, the reliability and performance of systems is considered one of the central interests in view of the enormous economic losses due to unexpected machine failures. For this reason, several maintenance strategies are adopted to maintain a system in working order and prevent these failures before they occur, such as CM, PM, Pd.M and reliability based maintenance. Although the concepts and mathematical foundations of these strategies are different, most maintenance actions aim to ensure a given level of system reliability that allows it to complete the remaining operations with maximum availability and without interruption [1, 2, 3].

In addition, such a system may include manufacturing equipment, aircraft, military vehicles, computer systems, power generation units, etc. In each of the above cases, the multi-component systems execute consecutive missions with scheduled intermission breaks devoted to maintenance operations. Although maintaining all components seems very expensive and sometimes unnecessary, selective maintenance aims to identify an optimal subset of components and the type of maintenance actions to be performed on the system to successfully achieve the next operation [4]. However, each of the available maintenance options expends some maintenance resources (time, budget, availability of repairman, etc..) so it is necessary to allocate these resources in an optimal way.

The problem of selective maintenance has been widely studied in the literature, most of the existing work has focused on model-based approaches in which system degradation follows a stochastic process. However, these suggested maintenance selective resolution methods are mainly based on theoretical analyzes and estimated parameters and do not necessarily reflect reality [5]. Moreover, even if a theoretical model is created, it cannot be directly applied in industrial practice where multiple operational variables exist and can affect the validity of the proposed model over time.

AI and ML techniques have recently been implemented in several industrial environments to overcome these problems encountered in model-based approaches. One of the applications of AI is the integration of ML and maintenance, in which companies rely on new types of maintenance for their machines. Such methodology uses predictive tools to estimate when maintenance is necessary. It continuously monitors machine conditions over time and allows for early detection of failures based on historical data [6].

Therefore, it is possible to collect massive amounts of real data generated from the various system components, and then learn relevant information patterns from this data to use the unhidden patterns for decision making in selecting the best components that need to be maintained and making an automated fault detection to minimize the downtime and related costs and increase the utilization rate of the components [7].

This project proposes a new multi-level selective maintenance approach based on a predictive model of a multi-component system by applying supervised ML tools, unsupervised ML methods and meta-heuristic optimization methods. Our methodology aims to establish an efficient selective maintenance policy exploiting historical maintenance data. Firstly, clustering algorithm is used to identify similar components having the same degradation behavior and then to determine the actual age for each component. Therefore, the a regression model was exploited to build the actual behavior model capable of predicting the real age of the component system based on the operational and real-world conditions such as maintenance actions number, maintenance type and mean time between failures, etc. The predicted component age is further used in the proposed optimization model to create an optimal maintenance plan.

The rest of the report is organized as follows. The first chapter presents a literary review related to the general context of the considered problem. Chapter 2 details the theory and background of the proposed predictive model for multi-level selective maintenance and we present some numerical results and their corresponding analysis. In the third chapter, we formulate the optimization problem and present the steps of the meta-heuristic algorithm adopted to solve the considered problem. Finally, the conclusion and the future works are presented by highlighting the major recommendations of the project.

Chapter 1

State of the Art and Literary Reviews

1.1 Introduction

This chapter presents the literary review on which we based ourselves and the project general framework. The main bodies of literature related to our study are SM and PdM (the model based and the data-based approaches) for system age prediction and maintenance plan determination. In this chapter, we explore some of the recent works related to our project before delving into our own contributions to this area.

1.2 Maintenance

1.2.1 Historical

Being a function at the service of other functions, maintenance was previously considered as a non-productive and therefore non-strategic function. Indeed, the role played by maintenance in industry has evolved considerably since the 1980s [8].

The concept “Reliability, Maintainability, Availability and Safety” has been integrated into the modern maintenance concept. This has created a new objective for scientific research in this field, which is the optimization of maintenance policies, particularly following appearance of the concept of PM [9]. The researchers essentially focused on three categories of maintenance policies.

A policy based on cost: Known by “Life Cycle cost LCC”, this strategy is strictly economic. It has been defined as a policy optimizing the overall cost of ownership during the life cycle of a product (research and development cost, design and manufacturing/production cost, operating and maintenance costs, scrapping and decommissioning) [10].

A policy based on reliability and maintainability: Also called “Reliability Centered Maintenance RCM”, or “Optimization of Maintenance by Reliability OMR”, this strategy is centered on the understanding of the functions of the equipment as well as the impact of their failures on the operation of the system.

A policy based on productivity: Known by “Total Productive Maintenance TPM“, this strategy is based on the participation of all staff in the maintenance. It opts for continuous improvement in the availability of equipment. TPM is mainly used for just-in-time.

1.2.2 Types

Maintenance actions can be classified into two main categories: CM and PM.

CM is performed when a system fails. These are then unplanned maintenance actions aimed at restarting the system regardless of the type of failure and its occurrence.

PM is performed while the system is in operation. These are actions planned according to the evolution of several parameters.

The study of the system allow to extract several parameters of its behavior especially in probability of occurrence in particular the probability of breaking down at each moment, probability of being in a given state of degradation according to time. System modeling is the use of these parameters to predict and plan interventions as well as to assess their costs.

These studies introduce a new categorization of maintenance: perfect maintenance, imperfect maintenance and minimal maintenance.

The perfect maintenance : These are replacement and repair actions that restore the system to a condition comparable to its new condition AGAN. Following such maintenance, the distribution of lifetimes and the failure rate are reset. It's the most expensive type of maintenance.

Minimum maintenance: The minimum maintenance actions have the sole purpose of restarting the system. Following a maintenance minimal, the system is said to be in as bad a state as before ABAO.

Imperfect maintenance: This category models an intermediate state between the two mentioned types. It was originally proposed in 1983 and defined as a simultaneous achievement of perfect maintenance and minimal maintenance with different probabilities[16].

1.2.3 Maintenance Policies

Based on the types of maintenance mentioned above, several policies have been incorporated. Some of these maintenance policies based on the time of functioning, namely block-type policies and age-type policies

The block type policy consists of setting up a system refurbishment schedule having the form kT ($k = 1, 2, \dots, N - 1$) time units, and replacing it at $N.T$ time units.

Thus, the objective of the strategy is to find the optimal parameters of the schedule; the optimal number of preventive maintenance periods N^* , as well as the optimal duration T^* of these periods, while minimizing maintenance costs.

During these periods, CM is carried out in the event of a system failure.

Age-type policy have the same principle than the block type except for the constancy of the size of the intervals T . Indeed, it consists in finding the optimal number of preventive maintenance N^* to be carried out before the replacement of the system and subsequently optimize the sizes of the N^* intervals. Given the importance of the number of decision variables and the correlation between them, this strategy is less used than there that of type blocks.

The strategies, described above, are the most basic. There are other more recent strategies using more important technologies including remote maintenance, total productive maintenance and reliability-centered maintenance.

Remote maintenance is based on the use of sensors linked to a control and monitoring unit and measuring the quantities linked to the state of the equipment in the system. Thus, thanks to the monitoring of the evolution of the state of the machines in real time, it is possible to determine the most appropriate type of maintenance.

Total Productive Maintenance, as defined previously, it consisted of the participation of all employees in the maintenance of the system. The complexity of this strategy is at the level of its prerequisites. Indeed, it requires employee learning and a corporate culture more than maintenance techniques

Reliability Centered Maintenance It focuses on the state of the system more than the changes to be made. It then consists of finding the optimum reliability threshold to minimize maintenance costs.

1.3 Failure Rate

The optimization of the different maintenance policies requires knowledge of the system failure which is related to the characteristics of the system equipment. In this context, three approaches have been proposed [11]:

The approach based on a physical model: This approach allow to precisely define the future state of the system provided that a mathematical formulation of the degradation mechanism is available. Given this condition, the approach based on a physical model is little used especially for complex systems. Some researchers have applied this approach in their work by considering degradation as a continuous variable whose evolution is determined by a deterministic or stochastic law [13].

The data-driven approach: This approach is based on the comparison of the parameters with the forecasts determined by statistical means. Indeed, the difference gives signs of deterioration of the system. Thus, it is guided by the data collected. In this context, the future state of the system can be defined using statistical methods.

The experience-based approach: If the definition of a mathematical model is complex and the monitoring of the System degradation is difficult, this approach is applied. It is essentially based on the reliable knowledge of the system, resulting from the feedback data of experiences.

1.4 Predictive Selective Maintenance

There are two main models of PdM : model-based and data-driven-based approaches

1.4.1 Model Based Approach

In the literature, the SM problem for multi-component systems was introduced by Rice et al. [13]. In this case, considering a series-parallel system with identical components, the only maintenance strategy available is replacement and the age of each equipment is exponentially distributed. In addition, to solve the SM problem, the system degradation process is modeled stochastically following an exponential or Weibull distribution which is more close to reality.

Otherwise, in many practical industrial conditions, the system health status and the parameters related to the lifetime distribution of the components after the execution of such missions are uncertain [14, 15] as well as the resources (such time allotted to the break and budget) required to perform maintenance actions are limited. So, the selective maintenance models have been used to increase performance and reduce life-cycle cost.

In addition, Chen et al [16, 17] proposed a new optimization approach to solve the SM problem for a multi-state series-parallel system. The components and the system are considered as multi-state systems which is more realistic than the binary component

assumption. The problem consists of minimizing the maintenance cost with transitions from one state to another for each component and the system.

Other SM studies proposed several maintenance options that can be performed to restore the component between AGAN and ABAO. These approaches are essentially based on age-reduction models or imperfect hybrid models that combine age reduction with hazard adjustment [18, 19]. In this work, the authors developed an age reduction model to represent imperfect repair for selective maintenance. They suggested that the age reduction factor depends on the maintenance cost, and a constant is used to reflect whether a component is relatively young or old. So the effective age of the component depends on this characteristic constant which helps to establish a relationship between age reduction factor, cost of maintenance, and effective age of the component.

1.4.2 Data Based Approach

However, all the above work is a model-based approach where the maintenance model is represented by some theoretical parameters. More recently, with the emergence of new technologies such as computer science and the Industrial Internet of Things, the maintenance strategies adopted in industrial fields are evolving towards a new PdM policy and condition-based maintenance [20, 21, 22].

The concept of PdM is to predict the future state of the system early enough based on its actual conditions. Several PdM approaches have been developed in the different production sectors in recent years. In [23] the authors proposed a new approach for predictive health management of manufacturing systems based on the component functional importance.

The idea of the predictive strategy consists of determining as first step the degradation mechanism, functional dependence and RUL for manufacturing. Then a mission reliability focused RUL prediction method for manufacturing systems is developed based on the functional dependency of the components. The selected maintenance strategy is based on dynamic RUL prediction after each maintenance action, and the functional importance is applied to prioritize the predictive maintenance component-sets. The proposed approach can ensure the ability of manufacturing systems to complete production tasks with high

quality products as well as reduce the maintenance cost.

Generally, the predicted maintenance framework consists of two parts : system age prediction and maintenance plan determination. Several methods and solution approaches from the research on the subject of selective maintenance for multi-unit systems have been studied. A set of criteria considered in selective maintenance optimization is proposed, including system characteristics, maintenance characteristics and mission profile characteristics. Based on these criteria, a general procedure for selective maintenance optimization is developed [24].

In this context, the data-based approach shows superior performance compared to the model-based approach since the latter requires prior knowledge of the system degradation mechanism, otherwise the data-based model uses real data to predict the system age without knowing the nature of the system degradation process [25]. Data-driven methodology requires several processing techniques to extract features from the collected data and to build the best model; such types of requirements involve manual data processing and analysis [26].

Although, deep learning approaches have provided an interesting opportunity to develop advanced prediction methods for maintenance data [27]. These models can automatically learn features and extract information despite high levels of abstraction in system data. In recent years, ANN have become widely used in prediction system age and machine failure detection [28, 29].

1.5 Summary

In this first chapter, we devoted a part to introduce the concept of maintenance, types and policies. we also presented a literature review of the selective predictive model for system age prediction and maintenance plan determination. In the next chapters, we detail the system model of the proposed approach. Then, we formulate the problem of the chosen model and use the adequate algorithm to solve it.

Chapter 2

Predictive Model for Multi-Level Selective Maintenance

2.1 Introduction

In this chapter, we start by detailing the main ideas of this project. Then, we will introduce the basic technical concept used in order to build the actual behavior model capable of predicting the real age of a given system based on its maintenance data. This is achieved using unsupervised and supervised ML techniques including k-means, SVR and ANN.

2.2 Project Goals

In industry, systems are subject to many degradation factors that impact their lifespan. As this degradation sometimes leads to a loss of resources (time and budget), the systems must be controlled and maintained according to their current state and the level of degradation. Furthermore, the objective in this project consists of selecting the best maintenance strategy to perform on each component according to the model predictions. The problem discussed in this work concerns the multi-series parallel system with n independent components $i = \{1, 2, \dots, n\}$. Such systems are required to perform successive missions alternated with intermission breaks devoted to carrying out selective maintenance actions.

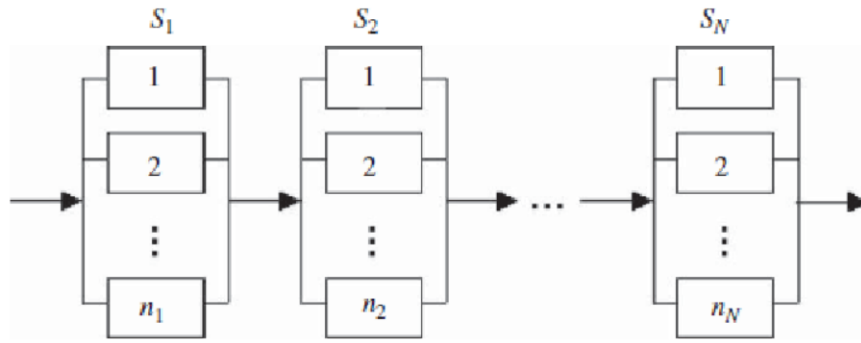


Figure 2.1: A series-parallel system

At the end of each mission, the system health condition degrades due to operating and environmental conditions. As such degradation level can lead to a system failure which can disrupt the operation chain and cause its unavailability, the degradation coefficients of the components should be predicted before starting the next mission according to the real conditions.

Then, these predictions will be used in order to select the best maintenance strategy that ensures a desired level of reliability and successfully completes the next operation. Fig. 2.2 illustrates the concept of the proposed selective maintenance approach.

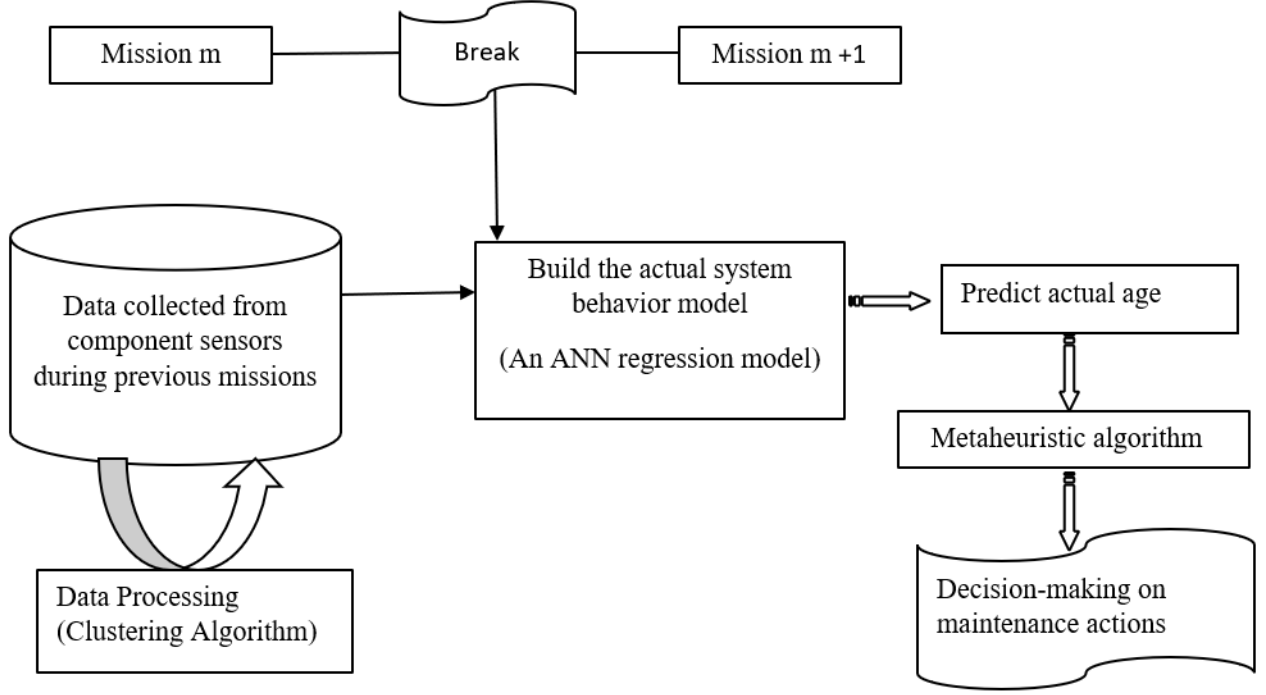


Figure 2.2: Overview the proposed maintenance selective approach

Considering that the age of a component A_i provided by the manufacturer does not consider the working and environmental conditions such as activity frequency, operating time, wear, etc. the proposed approach aims to determine the components real age γ_m^* by computing the age reduction factor b_i using k-means clustering algorithm. So, we suppose that the collected data during the operating time can be represented as a matrix form

$$X_i = [x_1, x_2, \dots, x_c, \dots, x_n] \in R_s * n$$

where $x_c = [x_c^1, x_c^2, \dots, x_c^s]$ is a s-dimensional vector of the component c features (Nb.CM, Nb.PM, MTBF, etc..)

Then, the system data collected during previous missions will be used to train the regression model. Next, the model is evaluated with a new data-set in order to be used during break in building the real system behavior and predicting the actual age components.

As the objective is to determine which maintenance actions should be performed on each component according to their predicted actual age, the obtained predictions are fed into the mathematical model in order to establish a maintenance plan that avoids failure and maintains the system reliability.

In addition, the following assumptions are considered to solve the proposed problem:

- Maintenance actions are performed only during the intermission breaks.
- The duration of missions and the breaks are assumed known and fixed.
- Imperfect maintenance actions can be performed on components during breaks.
- A minimum threshold of system reliability should be ensured throughout the operating period.

2.3 Theoretical Background

Several machine learning techniques have been used by different researchers to build predictive maintenance models based on maintenance data. An overview of the different algorithms used in this project is presented in this part. At first, we used a clustering algorithm to extract the similarity of the different components, then we aim to build a regression model capable of predicting the actual degradation coefficient. In the literature, K-means show a high performance in data analysis and clustering method [30, 31]. In addition, the ANN and SVR are those that have been the most used in prediction model in maintenance area, since the relationship between features is not linear, the techniques used were also nonlinear [33, 34].

2.3.1 Clustering Algorithm

Clustering is an unsupervised ML method in which we draw references from data-sets consisting of input data without labeled responses. Generally, it is used as a process to find meaningful structure, generative features, explanatory underlying processes, and grouping inherent in a set of clusters.

2.3.1.1 K-means

In this project, we used the clustering algorithm to group elements into a set of objects with similar characteristics, and then generate a significant feature: the degradation coefficient for each element using a specific calculation method which will be detailed in the next section.

Comparing to other clustering algorithms, K-means show high efficiency in classification and data analysis in which several methods are used, like Elbow method, silhouette method, and gap-stat method to evaluate the performance of this method [30].

The following algorithm summarises the main steps of K-means method:

Algorithm 1 K-means Algorithm

- 1: **input:** $\{x_1, x_i, \dots, x_N\}$ where x_i is vector containing the features of the element i
- 2: Set a fixed error threshold ϵ
- 3: Split data into K random objects. Let $(C_1, C_2, \dots, C_K)$ be the obtained groups and $(O_1, O_2, \dots, O_K)$ their representatives (the center of each class).
- 4: Calculate distance $d(O_k, x_i)$ between x_i and the different representative.
- 5: Assign the object x_i to the class k having the minimum distance $d(O_k, x_i)$.
- 6: **Update:** representatives of classes such as these new representatives correspond to the mean of class objects

$$O_k = \frac{1}{|C_k|} * \sum_{i, x_i \in C_k} x_i \quad \forall k, 1 \leq k \leq K \quad (2.1)$$

- 7: **Step 2:** if difference between the old and new representative is greater than ϵ
 - 8: **End**
-

The distance between the centroids of classes (mean of the vectors) used in Algorithm 1 is determined using Euclidean distance that is calculated as follows [32].

$$d(X, Y) = \sqrt{\sum_{i=1}^N (X_i - Y_i)^2} \quad (2.2)$$

2.3.1.2 Determination of degradation coefficient

In this part, we will determine the actual age by calculating the age acceleration factor using K-means algorithm which will be used in the next chapter to calculate the reliability system [29,30].

The used clustering algorithm allows to regroup system maintenance data into clusters according to certain features such as Nb.PM, Nb.CM, MTBF, ..etc. Each cluster i is rep-

resented by a centroid denoted by O_k and a set of components $C_1, C_2, \dots, C_s$. Indeed, to extract similarity between different components, each element i is associated with a distance between it and the centroid of the group to which it belongs.

Thus, the farthest element from the centroid of class it belongs to is the “bad-representative-component” although the “best-representative-component” O_M is the average of all clusters calculated by the mean of all centroids.

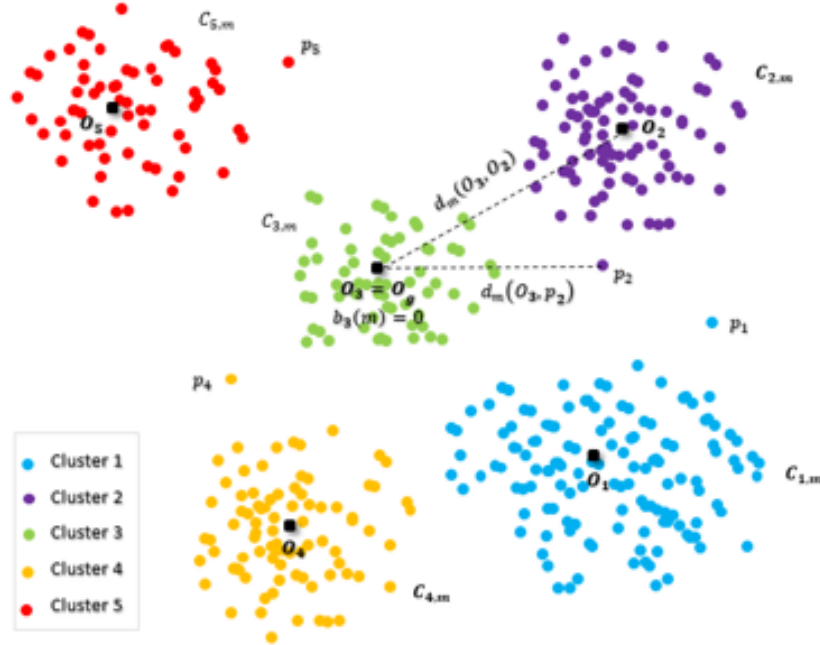


Figure 2.3: Calculation approach of coefficient degradation by K-means algorithm

So, the component degradation degree can be considered as its deviation from the “most representative component”. Consider L_i : the distance from the “best-representative-component” to the element i and l_i : distance between the best-component and the bad-component , the degradation coefficient is calculated as follows :

$$b_i = \min\left(\frac{L_i}{l_i}, \frac{l_i}{L_i}\right) , \quad 0 \leq b_i \leq 1 \quad (2.3)$$

Indeed if $b_i = 0$, is a null degradation degree where the component does not deteriorate and its actual age is that given by the manufacturer otherwise if b_i is very close to 1, is a maximum degradation, in such a situation the maintenance of component is necessary in order to avoid system breakdown.

2.3.2 ANN general concept

ANN are inspired by the architecture of neurons in the brain. To simplify the mathematical modeling, a neural network composed of a single hidden layer, an input layer, and an output layer, has been considered.

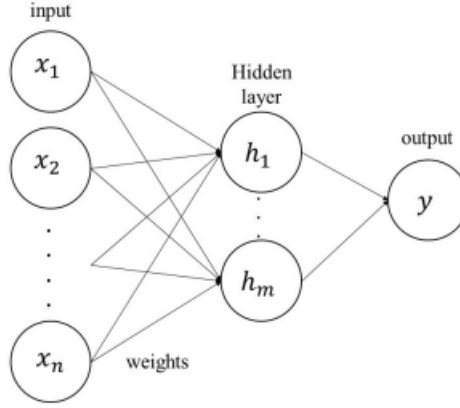


Figure 2.4: ANN structure

Nodes in one layer are linked to nodes in the next layer through weights. Initially, the weights and bias are randomly generated. The ANN model is based on the following equations:

$$h_{j,input} = \sum_{i=1}^n w_{i,j} * x_i + b_{input} \quad (2.4)$$

$$h_{j,output} = g(h_{j,input}) \quad (2.5)$$

$$y_p = \sum_{j=1}^m h_{j,input} + b_{hidden} \quad (2.6)$$

Where :

x_i the i^{th} input node

$h_{j,output}$ the output of the i^{th} hidden node

$w_{i,j}$ the weight connecting the input node x_i to the hidden node $h_{j,output}$

g the activation function of the model

b_{input} the input layer bias

b_{hidden} the hidden layer bias

y_p the model output: the estimated target value

A back propagation algorithm is then applied to the model in order to find the optimal values of the weights $w_{i,j}$.

An activation function in neural network is used to decide how the weighted sum of the input is transformed into an output from nodes in another layer of the network. The choice of activation function has a large impact on the performance of the neural network, and several activation functions may be used in different parts of the model.

In general, four common functions used in hidden layers which are considered as the activation function for the ANN algorithm:

Identity function

$$g(x) = x \quad (2.7)$$

Logistic Sigmoid Function

$$g(x) = \frac{1}{1 + \exp^{-x}} \quad (2.8)$$

Rectified Linear Unit Function RELU

$$g(x) = \max(0, x) \quad (2.9)$$

Hyperbolic Tangent function

$$g(x) = \frac{\exp^x - \exp^{-x}}{\exp^x + \exp^{-x}} \quad (2.10)$$

2.3.3 SVR general concept

This model is a kernel-based nonlinear learning technique used for regression as well as classification. It consists in defining or creating hyper-planes to discriminate predictions from training data. SVR approximates predictions using a function f that has a fixed deviation threshold from the actual targets [34].

The function has the following form:

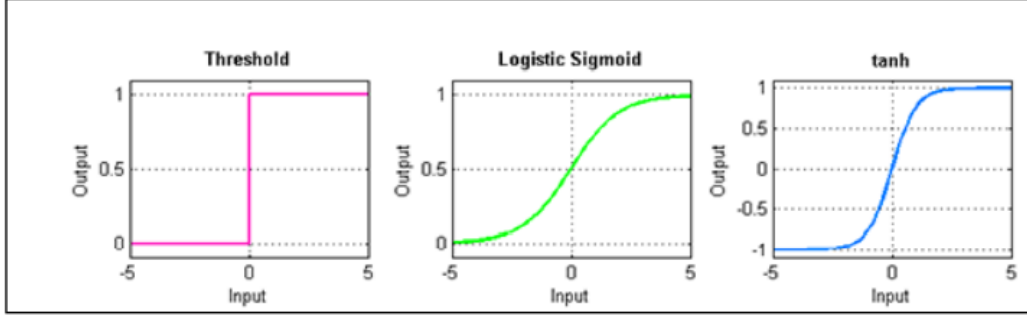


Figure 2.5: Non-linear transfer functions

$$f(x) = w * \phi(x) + b \quad (2.11)$$

Where ϕ is the transfer function, x is an input data point and the parameters w and b are estimated by solving the following optimization problem stated by Vapnik (1995) [34]:

$$\min \quad \frac{1}{2} * ||w||^2 + C \sum_{i=1}^n \psi_i + \psi_i^* \quad (2.12a)$$

$$\text{s.t.} \quad y_i - \phi(x_i) - b \leq \psi_i + \epsilon \quad (2.12b)$$

$$\phi(x_i) + b - y_i \leq \epsilon + \psi_i \quad (2.12c)$$

$$\psi_i, \psi_i^* \geq 0 \quad (2.12d)$$

Where y_i is the i^{th} target, n is the size of the training data, ϵ is the deviation threshold of the function f , C is the penalty parameter and ψ is the relaxed error that guarantees the existence of a solution under these constraints.

The Lagrangian form equivalent to this optimization problem (2.9) is given by:

$$f(x) = \sum_{i=1}^n (a_i - a_i^*) K(x_i, x_j) + b \quad (2.13)$$

Where $K(x_i, x_j)$ is the Kernel function and a_i, a_i^* is the Lagrangian multiplier. Four usual functions are generally used :

Linear function

$$K(x_i, x_j) = x_i^T * x_j + c \quad (2.14)$$

where c is an adjustable parameter

Polynomial function

$$K(x_i, x_j) = (a * x_i^T * x_j + c)^d \quad (2.15)$$

Where a , c and d are adjustable parameters.

Radial basis function

$$K(x_i, x_j) = \exp \frac{\|x_i - x_j\|}{\gamma} \quad (2.16)$$

hyperbolic tangent function

$$K(x_i, x_j) = \tanh((a * x_i^T * x_j + c)) \quad (2.17)$$

2.4 Hyperparameter tuning and model evaluation

In this part, we will detail the main steps to find the best configuration of the model. In fact, the process of training a model involves choosing the optimal hyper-parameters that the learning algorithm will use to learn the optimal parameters and correctly map the input features (independent variables) to the labels (dependent variables). Several training techniques introduced into machine learning to find these optimal hyper-parameters, the most widely used method is random search.

Indeed, this technique uses a random combination of parameters at each iteration to find the best solution for the built model. In addition, it has been shown theoretically and empirically a randomized search is computationally efficient, especially when it comes to ANN models [36].

There are many hyperparameters that should be tuned in an ANN unlike the other modeling strategies. Such hyperparameters are, the number of hidden layers, the number of neurons per layer, the type of activation function, and the training hyperparameters, like the learning rate, the batch size, the weight initialization. Then, a BP algorithm is applied to the model in order to find the optimal values of the weights $w_{i,j}$.

In this study, the hyper-parameters considered are the number of hidden layers, number of nodes for each layer and learning rate of the optimization algorithm used to fit the model. So defining the network configuration is the first step in developing the model. Therefore, compiling and fitting the network is the second step to build our model. The compilation applied an optimization algorithm to train the model and a loss function to evaluate the network.

As we studied a regression problem, an adaptive optimizer that is called Adam updates the network weights iteratively and a mean squared error loss function is implemented to calculate the average differences between the actual and predicted label [37].

Therefore, in order to evaluate the predictive performances and the accuracy of the model, certain evaluation indices have been used. These indices are among the most commonly used performance measures. To simplify index definitions, some notations are considered

$y_{m,i}$: the i^{th} actual value

$y_{p,i}$: the i^{th} predicted value

Absolute error: the absolute error is given by the absolute value of the difference between the measured value and the predictive value:

$$e_i = |y_{m,i} - y_{p,i}| \quad (2.18)$$

MAE measures the average of absolute errors of predictions and observations

$$MAE = \frac{\sum_{i=1}^n e_i}{n} \quad (2.19)$$

RSE measures the average squared difference between the observed and predicted values

$$RMSE = \sqrt{\frac{\sum_{i=1}^n e_i^2}{n}} \quad (2.20)$$

MAPE is a statistical measure to define the accuracy of a machine learning algorithm on a particular data-set, it can be considered as a loss function to define the error termed by the model evaluation

$$MAPE = \frac{\sum_{i=1}^n \frac{e_i}{y_{m,i}}}{n} \quad (2.21)$$

2.5 Numerical Results

In this section, we present numerical results that illustrate the performance of our proposed model . At first, we will present the model built in our experiments. Later, we will dive into the optimal hyper-parameters of the model. Next, we will discuss the metrics and evaluate the experimental results of prediction that we obtained.

In this project, we take the example of FMS situated at training and research unit mathematics, computer science and Mechanics (UFR MIM) of Lorraine university. This system is composed of eight stations. Each station is designed to perform an operation on a glass part: engraving by laser, temporary stock, two stations for assembling the engraved part with stand, quality testing, packaging, storage, and outing to the client. Fig.2.5 show the different stations of FMS.

Such a system contains 264 components, for each component are assigned certain maintenance activities and their characteristics recorded during the previous operating time (date of failure detection, type of maintenance (CM, PM), code error, etc.). Thus, the FMS data contains the record of all historical maintenance actions

Figure 2.4 displays some maintenance action recorded during last months.

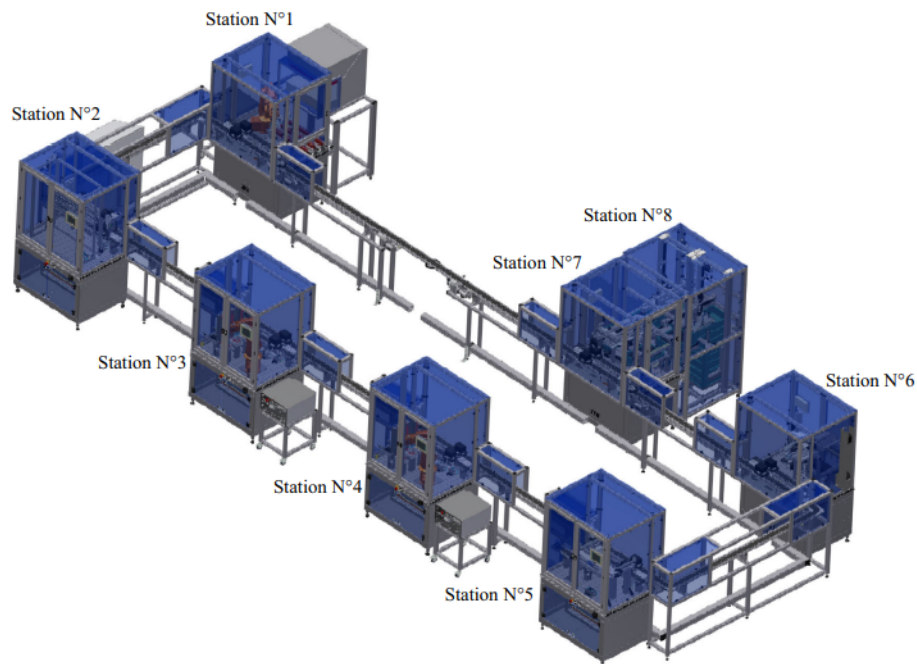


Figure 2.6: Flexible Manufacturing System

Time	Composant	code_error	type_maintenance
2022-01-02 00:01:31	AZ	le L	PM
2022-01-02 05:59:45	TT	kota	CM
2022-01-02 09:09:26	CY	anda	PM
2022-01-02 13:50:50	BY	yssa	CM
2022-01-02 15:50:33	KN	ne S	PM
...	...	...	...
2022-04-04 17:58:05	CL	tche	CM
2022-04-04 18:42:18	ST	am R	CM

Figure 2.7: Example of FMS data

Therefore, other features necessary to determine the actual age should be added such as the MTBF, Nb.PM and Nb.CM. After collecting maintenance data during the previous operating period, we apply k-means to classify components and then determine the coefficient degradation for each component. Figure 2.7. presents the results of clustering data with K-means.

As the main objective is to build a model able to predict the actual age of components from their real condition after performing some operations, these obtained results are fed into the ANN model for the forecasts. The process of prediction consists of three main steps: training, evaluation and use. (Eqs (14)-(21))

Firstly, the model has been developed in Python with the use of the Keras machine learning library on top of the open-source machine learning framework called TensorFlow. We choose python as a programming language because, in the recent years, Python has been known for its powerful packages used for a wide range of analysis needs and data mining. The data has been partitioned by 80:20 splitting rule, i.e. the 80 percent amount of the data constitutes for the training set, while the remaining 20 is employed to test the generalization ability of the model. Then, the info has been scaled to the interval of (0,1), which is understood to assist the neural network to learn underlying patterns both, more

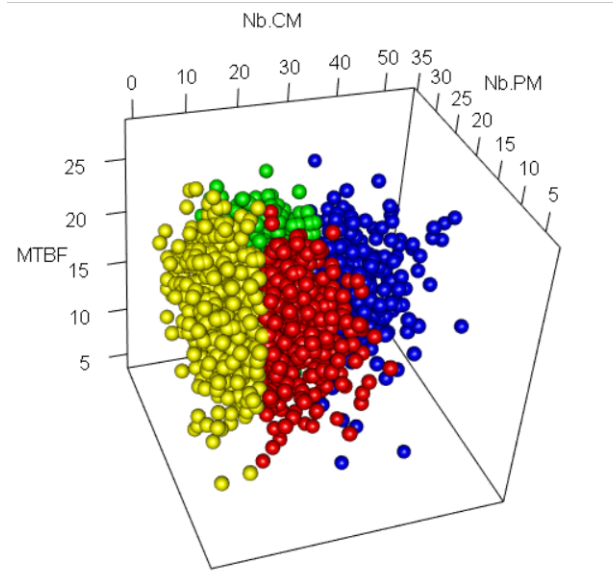


Figure 2.8: Results of clustering data with K-means

accurately and more efficiently.

To reach the optimal model hyperparameters, we use the random search method implemented in the Keras tuner library. So, the best configuration of the model found using the random search method is:

- an input layer of 3 nodes and an activation function Relu
- an hidden layer of 40 nodes and an activation function Relu
- an hidden layer of 20 nodes and an activation function Relu
- an output layer of one node (regression problem)

To evaluate the model performance in predicting the real age component after performing such operations, we use « evaluate » function which give us the train and test score of the model according to MSE loss function.

Table 2. shows the results of performance metrics for the ANN model on the FMS data-set compared to other regression models SVR.

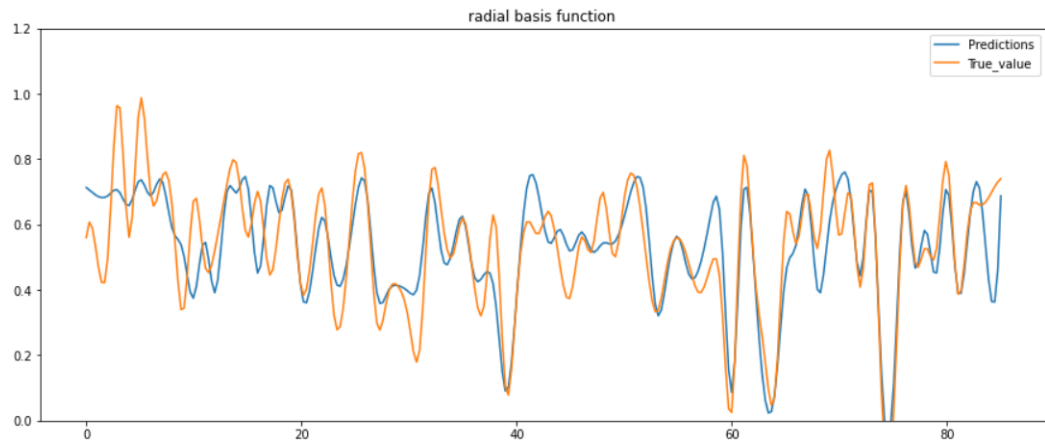


Figure 2.9: Actual Degradation Coefficient and predicted Degradation Coefficient With SVR - RBF Kernel

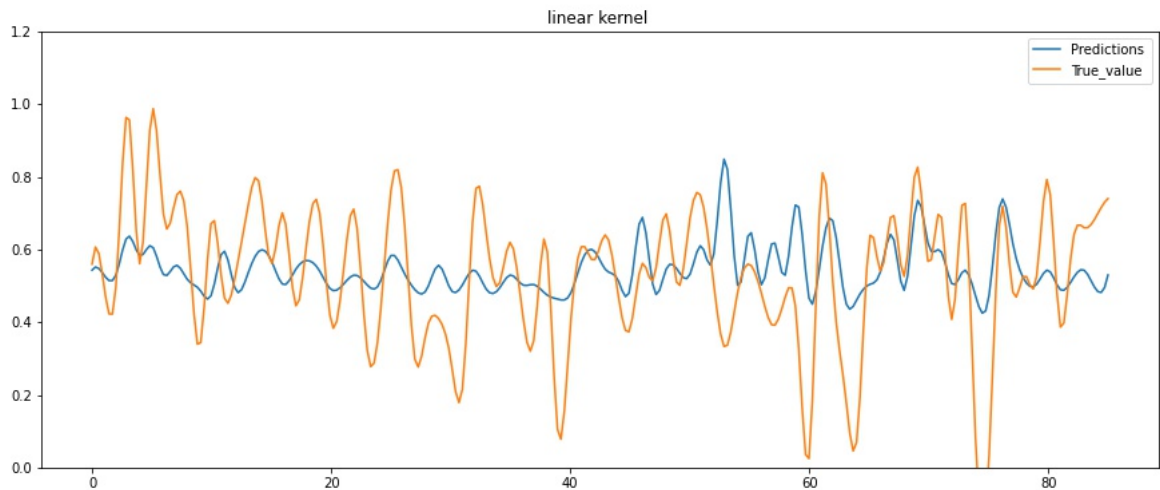


Figure 2.10: Actual Degradation Coefficient and predicted Degradation Coefficient With SVR - Linear Kernel

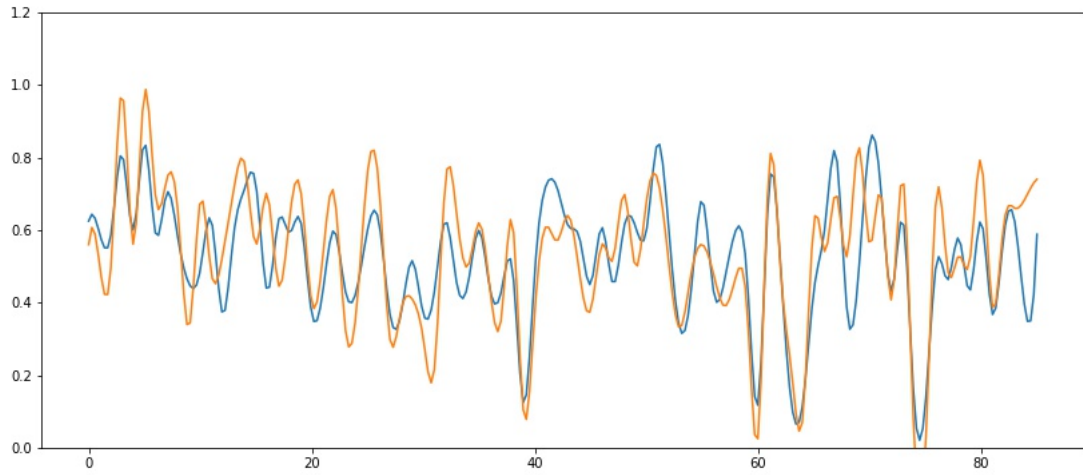


Figure 2.11: Actual Degradation Coefficient and predicted Degradation Coefficient With SVR - ANN model

Table 2.1: Results of performance metrics

Prediction method	RMSE	MAE	MAPE
SVR with linear Kernel	0.19	0.15	0.3
SVR with RBF Kernel	0.17	0.14	0.28
ANN	0.13	0.1	0.23

In addition, the results obtained revealed that the ANN model is more appropriate for predicting the true age than the SVR. Based on the previously defined performance measures, we can affirm that ANN is more efficient for the resolution of our problem.

2.6 Summary

In this chapter, we have focused on the prediction of system degradation. In fact, accurate forecasts allow maintainers to know the current state of the system and manage maintenance schedules. This guarantees the prevention of breakdowns. For this, we studied and implemented two machine learning techniques, SVR and ANN. We used maintenance data including MTBF, Nb.PM and Nb.CM to predict the actual age of the system. The simulations performed showed that, in the case of our problem, ANN is more efficient than the SVR method.

Chapter 3

Maintenance planning

3.1 Introduction

This chapter aims to establish a maintenance plan for a multi-component system based on the study of its reliability function. To this end, we will explore a real conditions data to determine the components failures and deterioration. Then, by minimizing the total maintenance cost of the system under reliability and time constraints, we will propose an optimal multi-level maintenance plan for a horizon of a few days.

In the industrial field, the maintenance system in working order has very high expectations, and in order to meet them, high efficiency and high reliability must be guaranteed. Thus, the reliability of the system must be studied and maintenance actions must be carried out. The planning of these actions must be optimized in order to minimize costs and maximize availability.

In this context, we will study the reliability of a multi-component system in order to establish a multi-level maintenance plan for a finite horizon.

3.2 Estimation of system reliability

In this part, we will determine the reliability system based on the failure rate which is calculated from the determined degradation coefficient.

First, the concept of reliability function based on the Accelerated Life Model(ALM) was introduced by Martorell and al.[38]. The proposed model consists in considering a covariates vector $g(Z)$ represents the risk function where Z contains the operating conditions represented by q covariates. Thus, the reliability function can be expressed as follows :

$$R_{ALM}(t, Z) = R_{nom}(g(Z) * t) \quad (3.1)$$

where R_{nom} is the nominal reliability in the case where no risk is considered $Z = 0$ and $g(Z) = 1$

In general, the $g(Z)$ is modeled by a log-linear function as follows

$$g(Z) = \exp(B^T \cdot Z) \quad (3.2)$$

where B^T corresponding to q coefficients associated with each covariate of vector Z . These coefficients are used to qualify the influence of each covariate on the degradation of system age.

Moreover, in the literature, several methods have been used to define the exact formulation of the risk function such example in [39], the author considers that the age acceleration was throw the action of imperfect maintenance and follows a probabilistic law.

In this project, we adapt the one proposed by Kammoun and al.[40] in which the function is given by the following formula:

$$g(Z) = \exp(-b_i) \quad (3.3)$$

where the covariate b_i representing the age acceleration factor. The method for determining the b_i is detailed in the previous chapter.

The actual age of components $\gamma_i^*(m)$ at the end of mission is calculated as follows:

$$\gamma_i^*(m) = A_i^*(m) * \exp^{-b_i(m)} \quad (3.4)$$

Where the theoretical age $A_i^*(m)$ at the end of mission m

Adding to that , the relation between the failure rate $\lambda_i^*(m)$ of a given component i and its actual age is defined by the following expression :

$$\lambda_i^*(m) = s_1 + s_2 * \exp^{-g_i * (\gamma_i^*(m))^3} \quad (3.5)$$

Where s_1 , s_2 and g_i are system settings depending on the equipment characteristics and its age degradation. Indeed, for such component have been maintained recently, the failure rate is close to s_1 . Otherwise, when the actual age decreases, the failure rate becomes higher until it reaches the sum $s_1 + s_2$.

In addition, the positive parameter g_i is introduced due to significant variation of the maintenance data and the real conditions which may occur during the period of operation such that the system age degrades when the g_i is important however the system have a low failure rate when the g_i is less significant.

Therefore, the system reliability function is considered closely related to the failure rate and takes into account the degradation of the system lifetime. So that, it can be expressed as follows:

$$R(\lambda_i^*(m)) = \exp^{-\int_0^{D_m} \lambda_i^*(m) dm}, \forall m \in [0, D_m] \quad (3.6)$$

where D_m is the mission duration m .

For components associated in series, the reliability of the group is assumed to be the product of the reliability of each component:

$$R_{sys}(m) = R_1(m) * R_2(m) * * R_n(m) = \prod_{i=1}^n R_i(m) \quad (3.7)$$

For equipment composed of different components associated in cascade, the system reliability can be calculated as follows:

$$R_{sys}(m) = (1 - R_1(m)) * (1 - R_2(m)) * * (1 - R_n(m)) = \prod_{i=1}^n (1 - R_i(m)) \quad (3.8)$$

3.3 Imperfect selective maintenance model

The failure rates increase due to the machine degradation. The role of the overhaul operation is to eliminate the effect of this degradation and improve the age machine. Since perfect maintenance is very expensive, in this part we assume that multi-level maintenance activities are possible in order to reduce the maintenance cost and time. We consider that maintenance operation improves proportionally the age of the system components compared to its value before maintenance activity.

The effect of maintenance action on the age of the machine is given by the following equation:

$$a^+ = a^- + \text{delta}_k^+ \quad (3.9)$$

Where delta_k^+ is the imperfect maintenance parameter equivalent to the age improvement value, a^- is the age of the machine before maintenance operation and a^+ is the age after maintenance operation.

The key idea is to model the case between the two extreme maintenance activities (overhaul and do nothing). Several intermediate maintenance strategies $k_i \in \{1, 2, ...K_{max}\}$ between ABAO and AGAN can be applied for each component i . Thus, each maintenance

policy k_i has an age improvement value, a known maintenance cost and duration.

Table 1 summarizes the different multi-level maintenance strategies considered in our problem .

Table 3.1: Possible maintenance strategies

Maintenance strategy k	age improvement value	signification
1	0	ABAO
$k_i = 2, \dots, K_{max} - 1$	δ_k^+	imperfect maintenance action
$k_i = K_{max}$	-	AGAN

3.4 Problem Formulation

3.4.1 Optimization Problem

In this part, we aim to optimally plan the maintenance actions of a multi-series parallel system S with n independent components C_i , $i \in \{1, \dots, n\}$. Our approach combines the two maintenance policies: policy based on cost and policy based on reliability. In fact, the problem consists in minimizing the total maintenance cost under reliability constraints. For this, the following notations are used for modeling the considered maintenance problem :

$MC(m)$ is the total maintenance cost during the break between mission m and $m + 1$.

C_a assembly or disassembly cost incurred if at least one component is maintained.

$A_i^*(m)$ theoretical remaining useful life of component i after performing mission m

$C_{i,k}$ is the cost of the maintenance strategy k performed on component i .

$d_{i,k}$ duration of the maintenance strategy k performed on component i .

$R_i(\gamma_i^*(m))$ system reliability associated with actual ages of multi-components.

σ_m break duration between mission m and $m + 1$.

A_i Theoretical component age i given by the manufacturer.

$\gamma_i^*(m)$ Actual age of component i at the end of the mission m .

R_{min}^* minimal required reliability.

d_m mission duration m

C_t repair cost per time

M Total number of missions.

Considering the problem of minimizing the total cost maintenance under the constraints of allocated resources (financial and time), the maintenance cost following the maintenance of component i is shared between its maintenance action cost and the workforce cost that can be expressed by

$$C_{k,i} + C_t * d_{k,i} \quad (3.10)$$

In addition, the cost of system disassembly or assembly in case at least one component is maintained during σ_m is given by

$$C_a * \phi_m \quad (3.11)$$

So that, the total maintenance cost $MC(m)$ after performing mission m is the sum of the maintenance costs of individual components which depends on the selected maintenance strategy and can be formulated as

$$MC(m) = \sum_{i=1}^n (C_{i,k} + C_t * d_{i,k}) * \delta_{i,k}(m) + C_a * \phi_m \quad (3.12)$$

where $\delta_{i,k}(m)$ and ϕ_m are the binary decision variables

$$\delta_{i,k}(m) = \begin{cases} 1 & \text{if the maintenance strategy } k \text{ is performed on the component } i \\ 0 & \text{else.} \end{cases}$$

$$\phi_m = \begin{cases} 1 & \text{if } \sum_{i=1}^n \delta_{i,k}(m) > 0, \forall k \geq 1 \\ 0 & \text{else.} \end{cases}$$

Assuming that maintenance actions are performed sequentially, the total time of all maintenance operations is the sum of maintenance duration of all maintained components. Since the down-times available to system maintenance is limited, the total duration of all maintenance actions must not exceed the intermission break time which must be respected as defined in the following equation

$$\sigma_m \geq \sum_{i=1}^n \delta_{i,k}(m) * d_{i,k} \quad (3.13)$$

For each component i only one maintenance strategy can be performed during σ_m as

defined in (2.5)

$$\sum_{k=1}^K \delta_{i,k}(m) = 1 \quad (3.14)$$

The problem consists in finding an optimal sequence of maintenance actions that provides the desired level of system reliability for each mission so that the reliability of the multi-component system $R_i(\gamma_i^*(m))$ for the mission $m + 1$ must be at least equal to a reliability threshold fixed R_{min}^* by the production stakeholders

$$R_i(\gamma_i^*(m)) \geq R_{min}^*, \forall i = 1, \dots, n \quad (3.15)$$

Thus, combining the above steps of all constraints gives the following formulated problem:

$$\min_{\mathbf{m}} \sum_{i=1}^n \sum_{k=1}^K (C_{i,k} + C_t * d_{i,k}) * \delta_{i,k}(m) + C_a * \phi(m) \quad (3.16a)$$

$$\text{s.t. } A_i^*(m) = A_i^* - \sum_{k=1}^K \delta_{i,k} * d_{i,k}(m), \forall i = 1, \dots, n \quad (3.16b)$$

$$\sum_{k=1}^K \delta_{i,k}(m) = 1, \forall i = 1, \dots, n \quad (3.16c)$$

$$\sigma_m \geq \sum_{i=1}^n \sum_{k=1}^K \delta_{i,k} * d_{i,k}(m) \quad (3.16d)$$

$$\gamma_i^*(m) = A_i^*(m) * \exp^{-\sum_{k=1}^K \delta_{i,k} * b_{i,k}(m)}, \forall i = 1, \dots, n \quad (3.16e)$$

$$R_i(\gamma_i^*(m)) \geq R_{min}^*, \forall i = 1, \dots, n \quad (3.16f)$$

$$\delta_{i,k}, \phi_m \in \{0, 1\}, \forall i = 1, \dots, n \quad (3.16g)$$

The objective function (2.7a) aims to minimize the total maintenance cost . Constraint (2.7b) calculates the remaining useful life of component i after performing mission m . Constraint (2.7e) calculates the real age $\gamma_i^*(m)$ of component i at the end of mission m . Constraint (2.7g) defines that decision variables are binary.

3.4.2 Resolution process

To solve the proposed selective maintenance problem (2.8), we used the EGD algorithm which is a meta-heuristic local search method based on two main steps initial solution construction at first, then neighboring solution construction. It is a process of randomly finding feasible solutions among all possible solutions and then repeating updating the current solution s with a new one s^* until some stopping criteria is satisfied.

In order to adapt the EGD to our problem, it is necessary to define an adequate representation of the solution and specify the type of neighborhood adopted. The research iteratively goes from one feasible solution to another by moves in the neighborhood. An overview of this algorithm is given in Figure 3.1 and the detailed steps of the resolution process to solve the optimization problem are listed in Algorithm 3. The procedure to construct the initial feasible solution is presented in Algorithm 1. The method adopted to find the neighbor solution is given in Algorithm 2.

Algorithm 2 Initial solution construction

- 1: set the length of S to a constant number K_{max} .
 - 2: generate randomly the elements of S from the set $\{1, \dots, P\}$.
 - 3: set $K = 1$
 - 4: calculate the objective function and the constraint values by using K first elements of S
 - 5: if $K = K_{max}$ and S is not feasible then go to step 2
 - 6: If $K < K_{max}$ and S is not feasible then set $K = K + 1$ and proceed from step 4.
 - 7: **End**
-

Algorithm 3 Neighboring solution

- 1: Choose randomly a number x from the interval $[0, 1]$.
 - 2: if $x \geq 0.5$ generate randomly two elements $S(i)$ and $S(j)$ of S with $1 \leq i \leq K$ and $K + 1 \leq j \leq K_{max}$ and exchange the contents of $S(i)$ and $S(j)$.
 - 3: if $x \leq 0.5$ choose randomly two elements $S(i)$ and $S(j)$ such that $1 \leq i \leq K$ and $K + 1 \leq j \leq P$ exchange the contents of $S(i)$ and $S(j)$.
 - 4: **End**
-

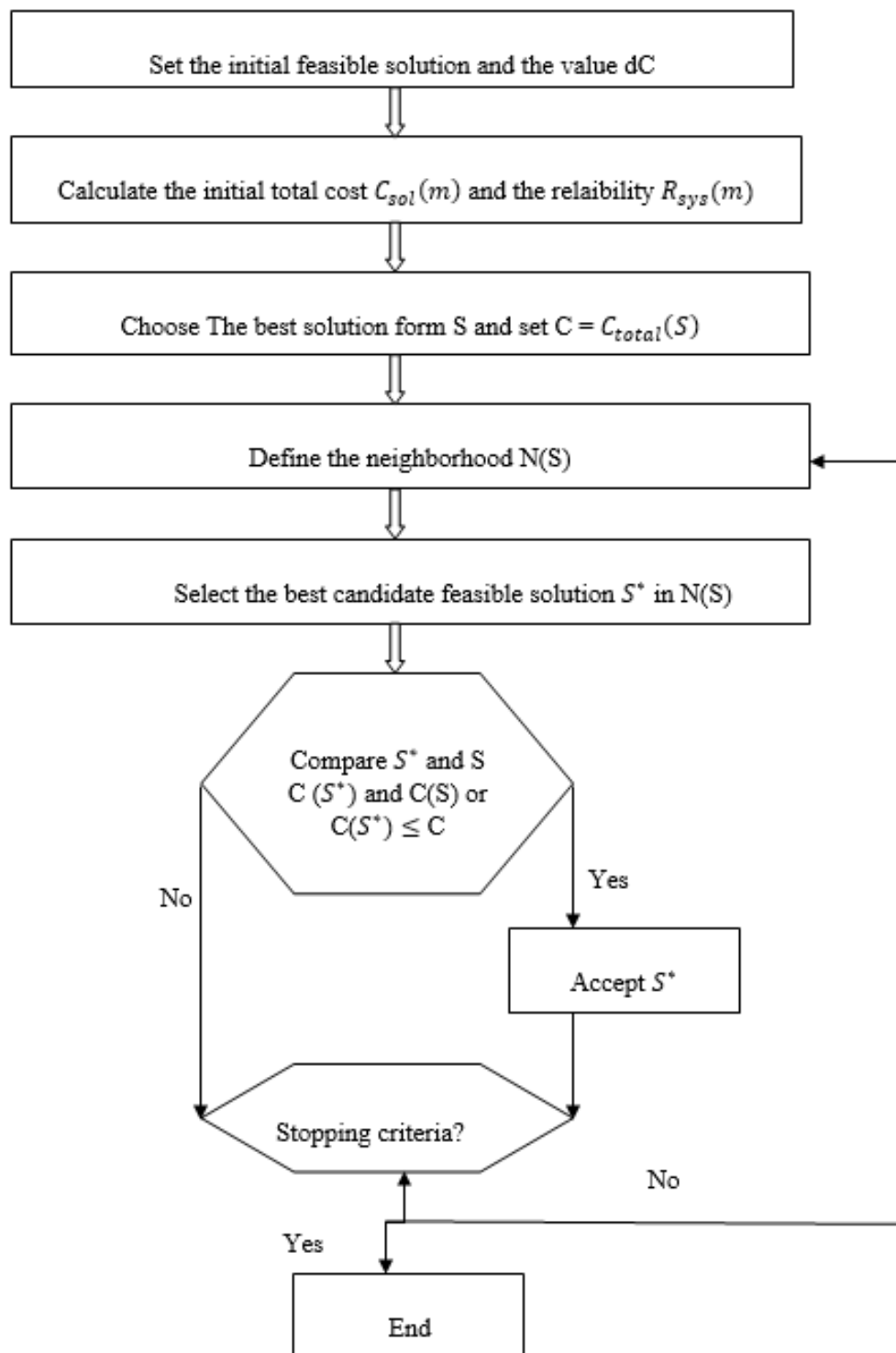


Figure 3.1: The overall resolution process

Algorithm 4 An overview of the EGD

- 1: set the initial feasible solution $\mathbf{s}$ and the value of $\Delta \mathbf{L}$.
 - 2: calculate the objective function $\mathbf{C}(\mathbf{s})$ and set $\mathbf{L} = \mathbf{C}(\mathbf{s})$.
 - 3: **Repeat**: until stopping criteria
 - 4: randomly select a feasible solution $\mathbf{s}^* \in \mathbf{N}(\mathbf{s})$
 - 5: if $\mathbf{C}(\mathbf{s}^*) < \mathbf{C}(\mathbf{s})$, set $\mathbf{s} = \mathbf{s}^*$ and $\mathbf{L} = \mathbf{L} - \Delta \mathbf{L}$
 - 6: **End**
-

3.5 Numerical results

In this section, we present numerical results that illustrate the performance of our proposed methodology. Indeed, we aim to obtain an optimal maintenance plan based on the model predictions. In this context, we feed the results obtained by the regression model into the meta-heuristic algorithm to select the best maintenance action for each component during intermission break which will guarantee the completion of the next operation without interruption.

Several maintenance operations considered in this part. Each strategy aim to proportionally improve the age of the component compared to its value before maintenance activity as well as its reliability. Thus, the objective is to select the best maintenance strategy that guarantees the achievement of the next mission with a level of reliability greater than 90%.

In addition, in order to illustrate our proposed methodology, a multi-series parallel system S selected from FMS data with nine components has been considered

$\{C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8, C_9\}$ to perform eight successive missions alternated with seven intermission breaks.

Fig. 5 present the system structure. The overall time operating is presented with the different missions and breaks in Fig. 6. The actual age of each component is given in Table 3.

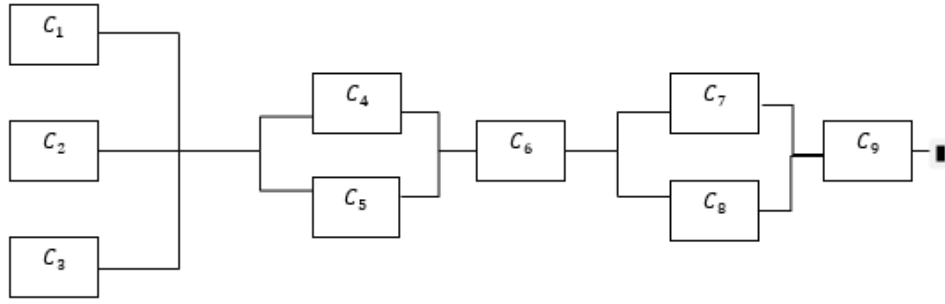


Figure 3.2: System configuration

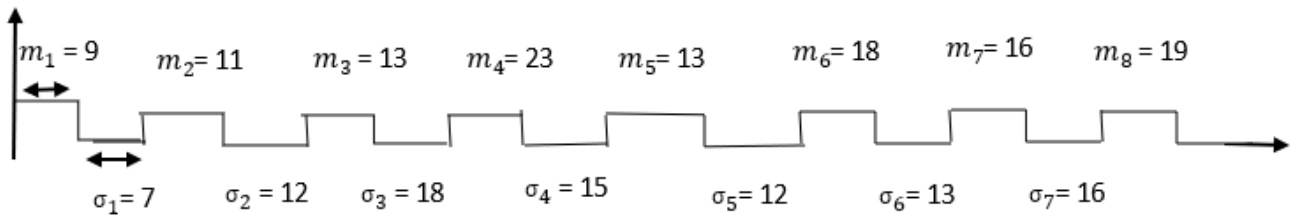


Figure 3.3: The overall operating time

Table 3.2: Parameters of system components

Component	$\gamma_i^*(0)$
C_1	136
C_2	140
C_3	135
C_4	135
C_5	128
C_6	130
C_7	129
C_8	139
C_9	140

As the number of available maintenance strategies depends on the system characteristics, we assumed that for each component five imperfect maintenance strategies are considered. The maintenance time and costs of each strategy are given in Table 4.

Table 3.3: Parameters of imperfect maintenance actions of component C_1

Component	Strategy	Age improvement	Cost	Time
C_1	1	0	0	0
	2	5	5	2
	3	17	12	3
	4	30	16	5
	5	replacement	22	7

To solve our problem of proposing a maintenance plan that minimizes the maintenance cost under reliability and time constraints we developed the algorithm based on the EDA approach on MATLAB software. The results obtained are summarized in Table 5.

As the actual predicted age of the components is quite high after performing the three first missions, the best maintenance strategy which is selected to be executed on the system during the breaks is strategy « 111 111 111 ». This means doing nothing for all components.

However, after completing the fourth mission, the age components deteriorate and the reliability system decreases, so by minimizing the total maintenance cost under reliability and time constraints, the best maintenance policy suggested by the mathematical model is performing Strategy 2 on Component 1, Strategy 2 on Component 5, Strategy 3 on component 6, Strategy 3 on component 8 and Strategy 1 for others components.

According to this strategy, the age of Component 1 is increased by 10, the age of Component 5 is increased by 7, the age of Component 6 is increased by 20, the age of component 8 is increased by 15 and no action is performed on the other components. The optimal policy results in a total maintenance cost of 116 and a total time of 13 and aims to achieve a reliability value equal to 0.9078.

In this case, the maintenance actions suggested using the mathematical model allow to provide the desired system reliability level (0.9) throughout the overall operating time. Fig. 7. shows the evolution of system reliability with the use of the proposed maintenance model.

The obtained maintenance plan during the considered operating time shows that the system reliability decreases during each mission. In order to maintain the system reliability higher than 0.9, the maintenance action selected at the end of mission allows to increase the components actual age as well as the reliability system, this increase is presented in Fig. 7 by an increasing line.

Otherwise, the system reliability follows an exponential variation during the operating time. As shown in Fig. 7, the maintenance action suggested by the proposed approach during the intermission break ensures that the system reliability respect the set threshold until the end of the mission.

Table 3.4: The best imperfect maintenance plan obtained for the required reliability level (0.9)

End of mission	Maintenance Strategy	Maintained Component	Maintenance Cost	Maintenance Time	System Reliability
m_1	111 111 111	do nothing	0	0	0.9898
m_2	111 111 111	do nothing	0	0	0.9896
m_3	111 111 111	do nothing	0	0	0.9868
m_4	211 123 131	$C_1 : s_2$ $C_5 : s_2$ $C_6 : s_3$ $C_8 : s_3$	116	13	0.9078
m_5	321 213 112	$C_1 : s_3$ $C_2 : s_2$ $C_4 : s_2$ $C_6 : s_3$ $C_9 : s_2$	132	12	0.9295
m_6	311 233 141	$C_1 : s_3$ $C_4 : s_2$ $C_5 : s_3$ $C_6 : s_3$ $C_8 : s_4$	178	13	0.912
m_7	521 323 111	$C_1 : s_5$ $C_2 : s_2$ $C_4 : s_3$ $C_5 : s_2$ $C_6 : s_3$	203	16	0.9087

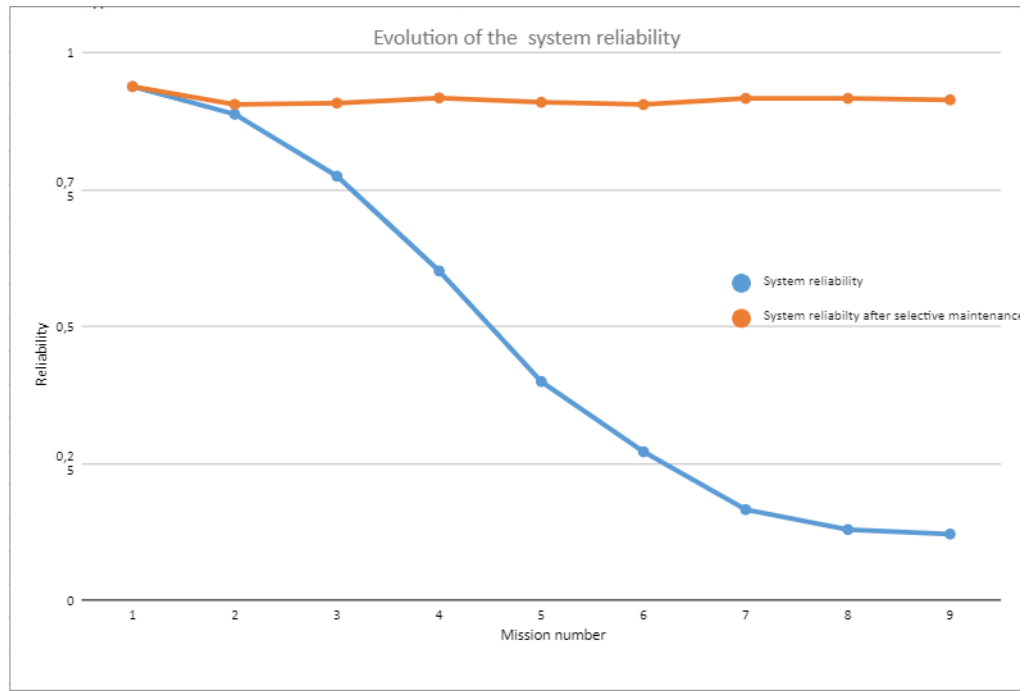


Figure 3.4: System reliability with vs without maintenance actions

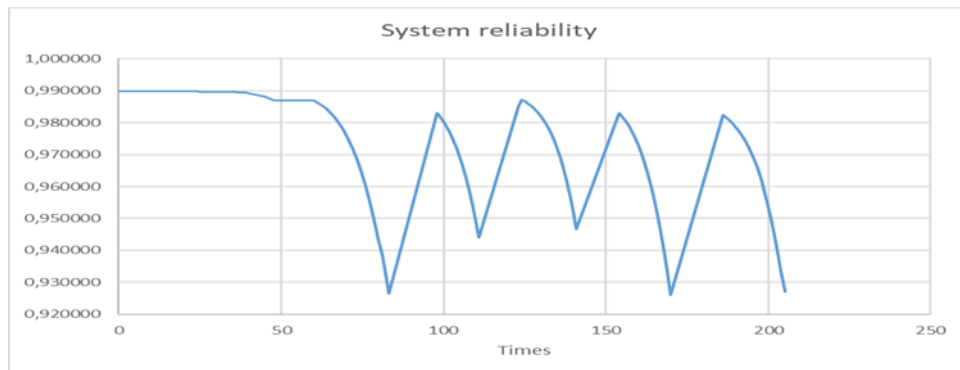


Figure 3.5: Evolution of system reliability after performing maintenance actions

3.6 Summary

In this chapter, we presented and detailed the approach that we proposed. We formulated the problem using some of optimization techniques. Finally, we presented our resolution process algorithm to solve the problem and then the numerical results.

Chapter 4

Discussions and Recommendations

Introduction

In this chapter, we discuss some environmental and social-economic impacts of our project. Then we explain its limitations before providing useful recommendations for the maintenance stakeholders.

4.1 Socio-Economic and Environmental Impacts

From an socio-economic impact perspective, a predictive maintenance program can bring significant savings and a noticeable return on investment. Eliminating breakdowns, increasing production and an overall return on investment, reducing maintenance costs and downtime are all results of a well-implemented predictive maintenance program.

However, a machine that is not well maintained is not always able to achieve optimum performance. In addition, a machine whose correct parts have not been replaced in the correct intervals, may break down completely with a worker in the middle. This happens on a regular basis, and while the examples are unfortunate, they underscore the immediate side effects we are seeing not only on performance, but also on managing the health of assets, manufacturing processes and ultimately on managing sustainability performance, because sustainability is first and foremost about worker safety and health.

4.2 Limitations

Given the limited time of the internship as well as the data available in the laboratory, we limited our project to study the case of a closed industrial system in which we did not take into consideration the impact of the environmental conditions on the degradation of the system and we assumed that the system actual age is influenced only by time factors and maintenance actions performed on system components which is not the real case in the industry field.

Another limitation of the project is the assumption that maintenance actions duration and costs are perfectly known and fixed which is not the case in real life and therefore the consideration of time lags or additional costs related to the error that may occur during maintenance operation needs to be accounted in future extensions of the current work. Moreover, this project was limited to the adaptation of a single meta-heuristic resolution method to solve the proposed multi-level maintenance problem since this methodology has been widely used in the literature in several imperfect maintenance problems and has yielded effective results.

4.3 Recommendations

Despite the advanced techniques and the huge amount of data available, most of the maintenance strategies adopted in practice, especially in Tunisian industry, are traditional and based on a planned maintenance program that does not take into account the historical data of the system.

However, in many studies, researchers have proposed several strategies based on data mining and machine learning techniques to estimate system degradation or predict the actual age of components, which helps maintenance stakeholders to elaborate an efficient maintenance plan. As in our project which presents a solution, that outperforms the traditional maintenance policies and proves to provide a valuable strategy that explore

maintenance data in order to study the system state and optimally maintain it.

In view of the numerical results highlighted in this work, we recommend that the maintenance manager adopt a predictive maintenance policy in their company to best maintain an industrial system and allocate the maintenance resources in an optimal way.

Summary

In this chapter, we discussed the social-economic and environmental impacts of our projects. We then highlighted its limitations and proposed some recommendations.

General Conclusion and Perspectives

Conclusion

In recent years, predictive maintenance has aroused great interest both in theory and practise than other existing maintenance strategies. In this context, the main goal of this project was the prediction of the real age system as first step and then the developing of the maintenance plan for an industrial system by exploiting the maintenance data provided.

To sum it up, the first part was dedicated to the prediction of failure rates from maintenance data. We exploited the results established in various works in order to choose the methods to be used. This pushes us to use SVR and ANN. The results obtained allowed us to conclude that ANN is the most suitable method for our input data and our system. Then, the second part was devoted to the study of system maintenance. We established its reliability function using a clustering method. We then integrated the degradation coefficients into the expression of reliability. Through the minimization of the total maintenance cost under the constraint of a reliability threshold 90% and the available time, we have proposed a multi-level maintenance plan for this system. This optimization has enabled us to achieve a reliability rate over 90%.

In addition, This work was concluded for the filing of a scientific article in waiting for acceptance and publication.

Perspectives

Some improvement can be added as perspectives. In fact, we will aim to integrate the factors of time and environmental conditions (temperature, pressure, humidity, etc.) into the prediction model. In addition, we plan to include other measures and criteria modeled by a multi-objective mathematical model. A future research direction would be to further implement more ideas using artificial neural networks and machine learning such estimate the probability that the system will fail and then integrate it into the maintenance planning.

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