



HAL
open science

Energy efficiency-based prognostics for optimizing the maintenance decision-making in industrial systems

Anh Hoang

► **To cite this version:**

Anh Hoang. Energy efficiency-based prognostics for optimizing the maintenance decision-making in industrial systems. Automatic. Université de Lorraine, 2017. English. NNT: 2017LORR0086 . tel-01588070

HAL Id: tel-01588070

<https://theses.hal.science/tel-01588070>

Submitted on 15 Sep 2017

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



AVERTISSEMENT

Ce document est le fruit d'un long travail approuvé par le jury de soutenance et mis à disposition de l'ensemble de la communauté universitaire élargie.

Il est soumis à la propriété intellectuelle de l'auteur. Ceci implique une obligation de citation et de référencement lors de l'utilisation de ce document.

D'autre part, toute contrefaçon, plagiat, reproduction illicite encourt une poursuite pénale.

Contact : ddoc-theses-contact@univ-lorraine.fr

LIENS

Code de la Propriété Intellectuelle. articles L 122. 4

Code de la Propriété Intellectuelle. articles L 335.2- L 335.10

http://www.cfcopies.com/V2/leg/leg_droi.php

<http://www.culture.gouv.fr/culture/infos-pratiques/droits/protection.htm>

THÈSE

Présentée et soutenue publiquement le 10 Juillet 2017
pour l'obtention du

Doctorat de l'Université de Lorraine
(spécialité Automatique, Traitement du signal et des Images, Génie Informatique)

par

Anh HOANG

Pronostic de la performance d'Efficacité Énergétique pour la prise de décision en maintenance dans les systèmes industriels

Rapporteurs:

Christophe Berenguer - Professeur à l'Institut National Polytechnique de Grenoble, France
Mitra Fouladirad – Maître de conférences (HDR) à l'Université de Technologie de Troyes, France

Examineurs:

Rossi Setchi - Professeur à l'Université de Cardiff, UK
Jay Lee - Professeur à l'Université de Cincinnati, USA
Olivier Senechal - Professeur à l'Université de Valenciennes et du Hainaut Cambrésis, France
Benoit Iung- Professeur à l'Université de Lorraine, France (Directeur de Thèse)
Phuc Do - Maître de conférences à l'Université de Lorraine, France (Co-directeur de Thèse)

Mis en page avec la classe thloria.

THESIS

Presented and publicly supported on July 10, 2017

to obtain the

Doctorate of Lorraine University
(Specialty Automatic, Signal and Image Processing, Computer Engineering)

by

Anh HOANG

Energy Efficiency-Based Prognostics for Optimizing the Maintenance Decision-Making in Industrial Systems

Reporters:

Christophe Berenguer - Professor of Grenoble Institute of Technology, France

Mitra Fouladirad – Associate professor of University of Technology of Troyes, France

Reviewers:

Rossi Setchi - Professor of Cardiff University, UK

Jay Lee - Professor of Cincinnati University, USA

Olivier Senechal - Professor of University of Valenciennes and Hainaut-Cambrésis, France

Benoit Iung- Professor of Lorraine University, France (Supervisor of Thesis)

Phuc Do - Associate professor of Lorraine University, France (Co-Supervisor of Thesis)

This page intentionally left blank.

Acknowledgements

First of all, I would like to express my greatest appreciations and thanks to my supervisor Professor Benoit IUNG, Lorraine University for his help, support, fruitful discussions, and encouragement that made this thesis possible.

My special gratitude is given to my co-supervisor Dr. Phuc DO, who accepted me as his first PhD student in Lorraine University, for his helpful and constructive comments, guidance and continuous support.

I am also in acknowledgement of funding by the Ministry of Education and Training, Vietnam (MOET) together with Vietnam International Education Development (VIED); without their financial support, this thesis would not have been a possibility.

Finally, I would like to express my great gratefulness to my family and friends for their consistent stimulation of my dream pursuit. I am deeply indebted to Trang Tran, my wife, for her persistent and timely sacrifice and cheer when I needed them the most.

Nancy, July 2017

Abstract

Among sustainability consideration, energy is today the key for economic growth in industrial systems. Energy resources are however limited and becomes more and more expensive. The energy optimization of manufacturing systems must therefore be considered as a major challenge to be compliant with environmental impact and management of energy resources. This should be reflected primarily by using energy efficiency (EE) as main key lever to deploy sustainability to plants, i.e. reduce the amount of energy required to provide products and services.

With regards to this EE context, the aim of this thesis is to investigate the problem of considering energy efficiency and its prediction as a new indicator in maintenance decision-making. In that way, we develop first a concept of energy efficiency, called EEI (energy efficiency indicator), applicable to the different levels of abstraction of an industrial system. Then, we propose a generic formulation to evaluate the EEI (and its evolution) taking into account static and dynamic factors of influence. The temporal evolution of this indicator with respect to the degradation of the system is addressed in a predictive maintenance objective. It leads to found an energy efficiency performance concept called REEL (remaining energy-efficient lifetime), representing the residual energy lifetime. To predict the potential evolution of the IEE to calculate REEL, a generic approach based on existing predictive approaches is also developed. Next, we investigate the use of EE in CBM maintenance decision-making. Finally, all these contributions are validated on the TELMA platform.

Résumé

Aujourd'hui, la maîtrise de l'énergie est la question prépondérante pour la croissance économique des entreprises industrielles. En effet, l'énergie est une ressource qui se raréfie et qui devient de plus en plus coûteuse. L'optimisation énergétique est donc un défi majeur que doit relever les entreprises et principalement celles manufacturières pour supporter les exigences du développement durable. Cette optimisation est à construire prioritairement par une amélioration de l'efficacité énergétique (EE), c'est-à-dire réduire la quantité d'énergie requise pour produire des produits et des services.

En regard de ce défi énergétique, l'objectif de cette thèse est d'investiguer la considération de l'efficacité énergétique et de sa prévision comme un nouvel indicateur pertinent dans la prise de décision en maintenance. En ce sens, nous proposons tout d'abord un concept de l'efficacité énergétique, appelé EEI (EE indicator), applicable aux différents niveaux d'abstraction d'un système industriel. Nous définissons ensuite une formulation générique permettant d'évaluer l'EEI (et son évolution) en prenant en compte les facteurs d'influence statiques et dynamiques. Cela nous amène à fonder un concept de performance d'efficacité énergétique, appelé REEL (Remaining Energy-Efficient Lifetime), représentant la durée de vie énergétique résiduelle. Pour prédire l'évolution potentielle de l'EEI qui permettra de calculer la REEL, une approche générique basée sur des approches de pronostics existantes est également développée. Ensuite, nous investiguons l'utilisation d'EE dans la prise de décision en maintenance conditionnelle (Condition-Based Maintenance, CBM). Enfin, toutes ces contributions sont validées sur la plateforme laboratoire TELMA.

Table of Contents

General Introduction.....	1
Chapter 1 An overview about energy efficiency in “green manufacturing” for maintenance decision-making.....	7
1.1. Introduction	7
1.2. From sustainability in general.....	7
1.3. To sustainability in manufacturing industry: Green manufacturing.....	10
1.4. What is energy efficiency in general ... and then in industry?	15
1.4.1. Energy efficiency in general	15
1.4.2. Energy efficiency in industry and mainly in manufacturing.....	16
1.5. How to integrate EEI/EEP in maintenance decision-making and more precisely in CBM?	19
1.5.1. Classification of maintenance strategies.....	19
1.5.2. Is Energy Efficiency already integrated in maintenance and mainly CBM?	23
1.6. Conclusions	24
Chapter 2 Scientific problem statement on EE concept and its application in CBM maintenance decision-making.....	27
2.1 Introduction	27
2.2 How to define and evaluate/predict EEI/EEP at the different abstraction levels of an industrial (manufacturing) system by considering the dynamics of this system?	27
2.2.1 General concepts of EEI and their application in manufacturing systems.....	27
2.2.2 EEI at each level of abstraction (component, function/system) of a manufacturing system	32
2.2.3 EEP concept for evaluating the residual life energy	37
2.2.4 Evaluation of EEI/EEP in dynamic context.....	38
2.3 How to use EE in CBM strategies?.....	39
2.3.1 Using EE as main condition for CBM strategies	39

2.3.2 Evaluation of the EE-based CBM.....	40
2.4 Conclusions	41
Chapter 3 EEI and REEL: concept and formulation for industrial applications.....	43
3.1. Introduction.....	43
3.2. Concepts of energy efficiency indicators for industrial systems.....	43
3.2.1 Energy efficiency indicator at component level.....	45
3.2.2 Energy efficiency indicator at the function/system level	47
3.3. Remaining Energy-Efficient Lifetime.....	49
3.3.1 Concept of the Remaining Energy-Efficient Lifetime	49
3.3.2 Evaluation of the Remaining Energy-Efficient Lifetime at component level.....	51
3.3.3 Evaluation of the Remaining Energy-Efficient Lifetime at higher level	53
3.4. Conclusion	55
Chapter 4 Generic approach for prognostics of the evolution of EEI and REEL.....	57
4.1. Introduction.....	57
4.2. Short review on existing prognostic approaches for RUL prediction	57
4.3. Global view of the proposed generic approach for prognostics of the EEI evolution and REEL	59
4.4. Step 1: Energy efficiency modeling.....	60
4.4.1. EEI at component level.....	61
4.4.2. EEI at higher level	64
4.5. Step 2: Prediction of the potential evolution of impact factors	65
4.5.1. At component level.....	65
4.5.2. At higher level	67
4.6. Step 3: Evaluation of the evolution of EEI and estimation of REEL	68
4.6.1. Phase 1: Evaluation of the evolution of EEI and estimation of REEL.....	68
4.6.2. Phase 2: Online updating of the Remaining Energy-Efficient Lifetime	69
4.7. Conclusion	69

Chapter 5 Validation of the contributions in the case of TELMA platform	71
5.1. Introduction.....	71
5.2. Presentation of TELMA platform	71
5.2.1 Identification and classification of key components and the function/system ...	73
5.2.2 Description of the system and experimentation	73
5.3. Implementation of the generic approach for selection of EEI and related models: architecture definition.....	75
5.3.1 Step 1: Energy efficiency modeling.....	75
5.3.2 Step 2: Prediction of the evolution of impact factors.....	82
5.3.3 Step 3: Evaluation of the potential evolution of EEI and estimation of REEL ..	84
5.4. Conclusion	85
Chapter 6 Use of EE for CBM maintenance decision-making.....	87
6.1. Introduction.....	87
6.2. General dicussions on EEI indicator for decision-making.....	87
6.3. EEI-based CBM maintenance	88
6.3.1. Maintenance decision rules.....	89
6.3.2. Extension of a classical CBM policy	92
6.4. Implementation platform TELMA.....	95
6.4.1. Maintenance optimization for MD1.....	96
6.4.2. Sensitivity analyses.....	98
6.5. Conclusion	101
General conclusion	103
Publications of the Author	107
Bibliography.....	109

Table of Figures

Figure 1. The three pillars of sustainability	8
Figure 2. Framework for Sustainable Manufacturing with the three pillars approach	11
Figure 3. Future manufacturing system with the integration of IT system	12
Figure 4. Multiple benefits of energy efficiency	16
Figure 5. EE contributing to TBL of sustainable manufacturing frameworks	17
Figure 6: Simplified classification of maintenance strategies.....	21
Figure 7. Structure of CBM decision-making	23
Figure 8. Concepts of EEI and their potential applications	44
Figure 9. Manufacturing system of 3 components.....	46
Figure 10. Illustration of the REEL and its variants	50
Figure 11. The REEL evolution at the component level.....	52
Figure 12. Procedure to evaluate REEL at function/system level.....	54
Figure 13. Classification of prognostic approaches	58
Figure 14. Generic approach for prognostic of the evolution of EEI.....	59
Figure 15. Generic approach for prognostic of the EEI evolution to estimate the REEL	60
Figure 16. Diagram for modeling energy efficiency of manufacturing systems.....	62
Figure 17. Procedure for prognostics approach selection of energy consumption and useful output modelling.....	63
Figure 18. Energy flow and Air flow output of fan system	64
Figure 19. Procedure for predicting the evolution of impact factors of the energy efficiency model	66
Figure 20. Procedure for selecting prognostic approaches to predict the evolution of a dynamic factor.....	67
Figure 21. Procedure to evaluate the evolution of EEIs and to estimate the REEL.....	68
Figure 22. Structure of the platform TELMA.....	72
Figure 23. Illustration of data sheet for recorded energy consumption.....	74

Figure 24. Real energy consumption of MD1 in relationship with speed and deterioration level	77
Figure 25. Calculated energy consumption of MD1 in relationship with speed and deterioration level.....	78
Figure 26. EEI of MD1 as a function of speed and bearing deterioration at the component level	81
Figure 27. A forecasted mission profile (a) and the bearing deterioration evolution of two motor-driven systems MD1 and MD2 (b)	83
Figure 28. Evolution of EEI at the component level (a) and at the function level (b)	84
Figure 29. Distribution of the REEL at $EEI_{Threshold} = 1030 \text{ Whproduct}$	85
Figure 30. Illustration of EEI evolution of one component and maintenance decision rules	90
Figure 31. Illustration of EEI evolution of system and maintenance decision rules	91
Figure 32. Behaviour of the maintained component under the (M,T) policy.....	94
Figure 33. Cost rate surface of the EEI-based CBM maintenance.....	96
Figure 34. Cost rate surface of the (M,T)-based CBM policy	97
Figure 35. Distribution of condition indicators at preventive maintenance time which is based on a) EEI level and b) conventional deterioration level.....	98
Figure 36. Total cost per product unit is a function of the preventive maintenance cost.....	99
Figure 37. Total cost per product unit is a function of energy price	100

Table of Tables

Table 1. Proposed KPIs of sustainability for different classified scales and levels of system ..	9
Table 2. The proposed measures of sustainable maintenance performance measurement systems	14
Table 3. The advantages and disadvantages of the categories of EEI to be applied in manufacturing systems [69].....	31
Table 4. Consideration of EE concepts at different levels of manufacturing.....	33
Table 5. The research gaps and industrial needs addressed in industrial system	36
Table 6. Parameters (α,β) of the bearing deterioration model of MD1 and MD2.....	83
Table 7. Energy and maintenance simulation parameter	96
Table 8. Optimal results of two CBM policies: EE-based CBM and (M,T) CBM maintenance.....	99
Table 9. Minimum total cost rate cost with different deterioration behaviours	101

Table of Abbreviations

CBM	Conditioned Based Maintenance
CU	Cost units
DF	Dynamic Factors
EE	Energy Efficiency
EEI	Energy Efficiency Indicators
EEP	Energy Efficiency Performance
EMS	Energy Management Systems
FoF	Factory of the Future
FOP	Future Operation Profile
IEA	International Energy Agency
KPI	Key Performance Indicator
PDF	Probability Density Function
PHM	Prognostics and Health Management
REEL	Remaining Energy-Efficient Lifetime
RUL	Remaining Useful Life
SF	Static Factors
TBL	The Triple Bottom Line
VSD	Variable Speed Drive

General Introduction

Nowadays, “Energy” is the key lever for economic growth. Indeed, industrial companies with complex manufacturing/producing/servicing activities may demand a huge amount of energy consumption. Nevertheless, energy resources are now limited and become more and more costly. Therefore, energy optimization of industrial plants (manufacturing or assembling lines, auxiliary system, etc.) is a major issue to their economic competitiveness, and their environmental impact. It is always true because “advanced” industrial system such as those advocated by Industry 4.0 or Factory of the Future initiatives are now organized from different abstraction levels, each one composed of numerous components (e.g. software, hardware, humans ...) interacting with the others to achieve the mission. It means that most of industrial systems, especially advanced manufacturing systems, are very complex and structured on multiple-layers in which the energy is very difficult to be mastered and/or optimized. This energy control is one factor to support sustainability and can be reflected primarily by considering Energy Efficiency (EE) as a Key Performance Indicator (KPI) to pilot plants, i.e. reduce the amount of energy required to provide products and services. This consideration is well in phase with European challenge because Europe has set ambitious goals to promote the development of new methodologies, new technologies or disruptive technologies improving the Energy Efficiency and reducing energy costs up to 20% in the most energy-intensive industrial sectors (manufacture of glass, cement, steel, refining...)[1].

This challenge has to support the way from controlling the industrial systems not only with regards to conventional performances or services (e.g. reliability, productivity) but also to emerging ones such as those representative of sustainability requirements [2]–[4]. Indeed, by integrating new sustainability KPIs, such as EE, in the decision-making process of industrial systems, the performance should be satisfied and optimized jointly with regards to the three fundamental pillars: Economy, Environment and Society. In manufacturing area, these pillars led to promote “Green Manufacturing”, “Green Production” frames. Nevertheless, EE is not really associated today with decision-making in industry. Several reasons can explain this fact. Current works on EE are focusing mainly on isolated EE properties (e.g. energy consumption, energy saving) without clearly define its concept as a whole and how to measure really Energy Efficiency Indicators (EEI). Indeed, even if some methods to assess EEI exist, they are

addressing principally EEI values at the component level (operational level) without considering it (for example by aggregation) at the system one which can be better for performance optimization (strategic level) [5], [6]. Moreover, this assessment is not easy to do because it should take into account the dynamics of the system (age, degradation, different loading profiles, etc.) impacting the EEI value and leading to track its evolution in the future to clearly define the Energy Efficiency Performance (EEP). The EE Performance is a performance materializing if the industrial system is efficient or not (it is more than a value; it is the value in time). The formulation of these EEI and EEP items is not evident [7] especially with regards to dynamic context (dynamics of the systems) for predicting the EE evolution in the same way as it was done through the use of conventional prognostics approaches to predict the Remaining Useful Life (RUL) of components/systems [8]–[11]. Thus, one important challenge in link to these required formulations is *“How to define and evaluate/predict EEI/EEP at the different abstraction levels of an industrial (manufacturing) system by considering the dynamics of this system?”* (Challenge n°1).

The results of these formalizations can be then integrated in the decision making processes of the industrial system to master the EEI/EEP as close as possible on its nominal value for controlling Environmental Pillar. More precisely this mastering requirement can be supported by the maintenance decision-making process as advocated the Prognostics and Health Management (PHM) community [12]–[14]. Indeed, an efficient maintenance strategy could not only avoid the failure of the system but also allow to anticipate the growing up of global energy consumption. Nevertheless, the current maintenance decisions are mainly based on conventional indicators such as reliability, availability, direct cost, etc. [15] and only just some investigations have been realized to consider the relationships between EEI and maintenance strategy [16], [17]. This relationship opens up a new path to define/adapt the “condition” to trigger the maintenance according to sustainability requirements and the evolution of their values (to promote originality towards EEP). In that way, specific condition-based maintenance strategy as CBM should be adapted to take into account EE-centered condition. Thus a second important challenge with regards to this required adaptation is *“How to use EE into CBM strategies?”* (Challenge n°2).

In summary by referencing to the two challenges previously underlined, the core idea, we defend in this thesis, is addressing the necessary evolution of CBM decision-making process in industry by integrating EEI/EEP to support sustainability requirements. This idea is built on 2

major scientific directions. The first one is related to the foundation of the concept of EEI and its evaluation/prediction (EEP) with regards to the industrial system operation. It is structured on several scientific issues as *Definition and formalization of Energy Efficiency Indicator - EEI usable in decision-making process of industrial (manufacturing) system (Scientific issue n°1)*; *Definition and formulation of energy efficiency performance (EEP) to estimate the residual life energy of a component/function/system (Scientific issue n°2)*; *Development of generic approach to support prognostics for predicting the evaluation of EEI at different levels of manufacturing system (Scientific issue n°3)*. The second direction concerns the integration principle of EE in maintenance decision-making and the control of the performance obtained. It is referred to another scientific issue which is *Foundation of EE-based CBM (Scientific issue n°4)*.

These scientific issues have been attacked during the Ph.D. period to provide 5 main contributions: (1) Foundation of a relevant EEI concept at component/function/system level of a manufacturing system; (2) Proposal of a generic formulation to be able to calculate EEI (and its evolution) by taking into account static and dynamic factors of the system at each abstraction level; (3) Proposal of an EEP concept, namely REEL (Remaining Energy-Efficient Lifetime) representative, from the EEI evolution, of the remaining time before a system loses its energy properties under a limit threshold; (4) Development of an appropriate generic approach based on different logical steps needed to concretize the EEI generic formulation to a specific industrial case; (5) Investigation on the use of EE in CBM maintenance decision-making, thereby evaluating the effectiveness of the EE-based CBM policy to offer inputs to optimization.

In regard of these main contributions, the thesis is structured into six chapters as follows:

Chapter 1 provides an overview about the consideration of sustainability in decision-making process mainly in maintenance phase of industrial (manufacturing) system [18]–[21]. So, it is started with positioning sustainability in general, then by underlining its three main pillars and the key performance indicators of each pillar. Moreover, the use of these KPIs in the industrial area, mainly manufacturing one, is investigated. It leads to focus on EE items such as EEI and EEP, and mainly their considerations in maintenance decision-making process. This consideration aims at isolating the two main industrial challenges related to the interest to clearly formalize EEI/EEP at different levels of a manufacturing system, and the integration of EE into CBM.

Chapter 2 aims at identifying the scientific issues related to each of these two challenges. So, the chapter 2 is focusing first on the definition, measurement of EE but also its prediction to be usable in decision-making and especially for CBM maintenance decision-making [22], [23]. It leads to underline issue related to the development of a consistent and pertinent EEI concepts at multi-levels of an industrial system, but also the generic formulation of EEI taking into account system dynamics (in terms of generic impact factors) (*Scientific issue n°1*). This formulation should integrate time-dependent conditions to propose all the set of variables usable in the prediction of the EEI evolution. This EEI evolution leads to investigate EEP assessment in terms of the residual life energy (*Scientific issue n°2*). Then, the generic formulations must be concretized, detailed ... according to a specific manufacturing system to allow a concrete EEI calculus (at time t), but also its evolution tracking. This concretization, detail ... phase has to be developed from a generic approach (*Scientific issue n°3*) integrating all the steps from the specific impact factors selection until the EEP assessment.

Finally, to keep the EEI/EEP as closed as possible to their optimal values space, evolution of maintenance strategy has to be investigated to integrate these indicators as a condition to trigger the maintenance as advocated more conventionally by CBM (*Scientific issue n°4*). These 4 scientific issues are addressed in the next chapters to present the thesis contributions.

More precisely, chapter 3 aims at describing contributions related to the two first scientific issues. In that way, the first contribution concerns the foundation of an appropriate EEI concept for manufacturing system (specific class of industrial system) and usable at different system abstraction levels. It comprises the definition of EEI based on two main aspects of EE properties: Energy consumption and physical useful output. These two properties represent variables to be mastered in the decision making-process. In addition, generic EEI formulation, usable at each level, is proposed. This formulation is described as the ratio between two parts in which time-dependent factors (called static and dynamic factors) are considered. The first part concerns the different types of energy resources consumed (as inputs). The second part concerns manufactured products provided (as outputs). Formulation can serve latter to calculate EEI value and also EEI evolution (due to the time-dependent factors).

Finally, with regards to the second scientific issue, it is proposed a novel concept named REEL (Remaining Energy-Efficient Lifetime) based on EEI evolution and representing the duration from the current time (in efficiency zone) until the predicted time when the manufacturing system is going to work in non-efficiency zone. Then REEL is considered

equivalent to EEP to present an important EE properties of manufacturing system in the context of this thesis.

Chapter 4 aims at tackling the scientific issue $n^{\circ}3$ related to an approach allowing to implement different steps required to use the generic formulation for EEI calculation on a specific manufacturing system and then to assess REEL.

So, it is proposed a generic approach structured on 3 main steps. In the first step, it is planned to clearly define, at each level of the specific manufacturing system, the energy consumption (as input) and the useful manufactured product (as output). It is also determined, for each level, the impact factors (static and dynamic) which have to be taken into account. Then, it is sought existing models integrating the identified factors and to be used for each part of the formulation (energy consumption, output). If adequate model for energy consumption and/or output is not available, model(s) should be created. Finally, from all the models, specific formulations (EEI models) are developed at each level to calculate the corresponding EEI value (at t time).

The second step of the procedure is dedicated to select and to implement the prognostic method the most appropriate for predicting the evolution of each impact factors. So, the whole of these evolutions obtained at the end of this step, are re-integrated, at the third step, in the specific formulations (expressed in step 1) to evaluate, now, the EEI value at any time in the future (EEI evolution). From this EEI evolution, it is assessed the remaining time before the system lost its energy properties under a limit threshold (REEL calculus).

Chapter 5 aims at validating the contributions proposed in chapter 3 and 4 by applying them on TELMA platform. TELMA is a platform materialising a physical process dedicated to unwinding metal strip. This process is similar to concrete industrial applications such as sheet metal cutting and paper bobbin cutting. The physical process is divided into four parts: bobbin changing, strip accumulation, punching–cutting and advance system. Each part consists of several components such as pneumatic cylinder, chuck, marking system, motor, etc. This first step of validation phase is mainly focused on the two independent motors at component level and consuming only electrical energy. Thus, EEI models issued of the implementation of the first step of the generic approach (chapter 4) are build from field data acquired on the motors (one EEI model per motor) completed with data related to the function achieved by these motors (one EEI model for the function). These models integrate impact factors such as bearing deterioration (dynamic factor) and mission profile (static factor). So data-driven based

prognostics is selected for predicting the evolution of bearing deterioration, and mission profile is fixed in advance by considering production plan. These factors evolutions allow to calculate the EEI evolution for each motor and the considered function leading to assess the REEL of these items.

Chapter 6 is finally focusing on scientific issue $n^{\circ} 4$ by investigating the interest of integrating EE into CBM decision-making. The investigation is focusing mainly to propose a new EE-based CBM model by using EEI value as a condition (and not yet the EEP value). Thus the main idea of this EEI-based CBM is to inspect, at specific time, the energy consumption, and output values in the way to calculate EEI and to trigger or not actions. Indeed, a preventive maintenance action is triggered if the EEI value is higher than a preventive threshold. Both inspection time interval and preventive thresholds are decision parameters to be optimized. Thus, corresponding with the EEI value of each individual component and the EEI value of a group of component (at function/system level), two main EEI-based CBM strategies are proposed (called individual maintenance and grouping maintenance). In the way to compare the benefits of this new EEI-based CBM strategy with conventional CBM one, an extension of an existing cost-model of CBM has been done by taking into account not only the maintenance costs but also the energy cost. The extended model leads to consider energy directly in the maintenance optimization. The comparison step is developed on the case study of TELMA platform allowing to assess the impact of EE on existing CBM strategies and to conclude on the interests of a new EE-based CBM practice in terms of cost optimization.

Finally, a general conclusion summarizes the overall research results detailed in this thesis, and it is discussed some future works based on extension of those done but also on future perspectives.

Chapter 1

An overview about energy efficiency in “green manufacturing” for maintenance decision-making

1.1. Introduction

The aims of this chapter is to provide an overview about the sustainability consideration in maintenance in the way to place the global context of the thesis. First, sustainability is introduced in general by positioning the three pillars concept and then the attached KPIs to it. In addition, sustainability consideration in industrial areas with a specific focus on manufacturing sector is investigated. It allows to isolate energy efficiency (EE) and its derivate EEI/EEP items as emergent KPIs to achieve both sustainability and optimized performances of maintenance. Moreover, the assessment of EEI/EEP in the case of manufacturing system and their study in maintenance decision-making process are surveyed. It leads to conduct an investigation into the formalization of the EEI/EEP applicable at different levels of manufacturing system, and then the interest to use EE as the “condition” for maintenance decision-making, mainly CBM one. All the previous considerations enable to underline in this chapter, the two mains industrial challenges on which the thesis is based.

1.2. From sustainability in general...

Recently, sustainability or sustainable are mentioned in a huge amount of studies and seen as a main key factor for success in the competitive business environment. The interest in sustainability has broadened according to people and other stakeholders concern. It is recognized as an important concept for survival in the competitive business environment [24]–[27]. However, there are different concepts and usages of sustainability at different domains, and it cannot be defined by a single universal term. Indeed, various studies mentioned “sustainability” under different aspects such as: “*Sustainability development that meets the needs of present without compromising the ability of future generation to meet their own needs*” (report of World Commission on Environment and Development in 1987 [28]); “*Sustainability performance can be defined as the performance of a company in all dimensions and for all drivers of corporate sustainability*”[29] or “*can be presented by the ability to reduce the waste, cut-down the energy*

footprint”. Sustainability related to improving overall sustainability include site planning, energy efficiency, water efficiency, indoor air quality, materials and resources [30]... Bretzke and Barkawi [31] defined “sustainability means that prevention takes precedence over containment and reparation”. In general, most of these definitions consider economy development, human/society and environmental protection as three main dimensions involved in the sustainability. They are often described and referred in the Triple Bottom Line (TBL) as shown in Figure 1[32] and selected as sustainability definition frame for this thesis.

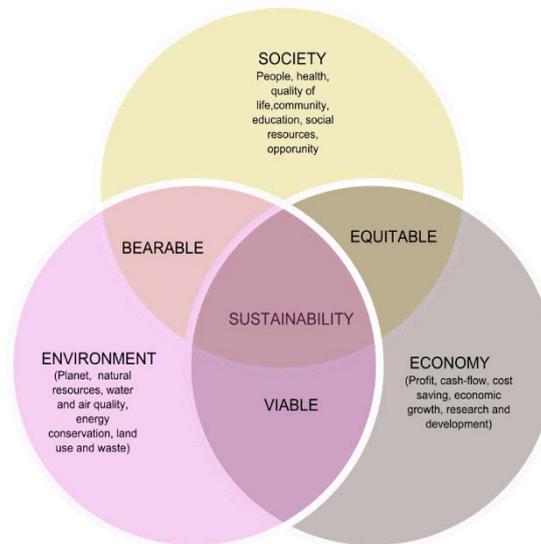


Figure 1. The three pillars of sustainability

With regards to this TBL, sustainability practitioners are becoming more ambitious in their sustainability efforts and are working together to share best practices to ensure the greatest environmental, economic and social impact. However, an important problem of the application of sustainability for one particular system is that the evaluation of the sustainability performances of industrial systems is extremely complex. It is difficult to measure or estimate precisely the sustainability [31]. Then, in order to assess the sustainability of one system, the use of sustainability indicators as Key Performance Indicators (KPIs) is necessary.

The KPIs should covered all the aspects of the TPL and is useful for monitoring changes in system characteristics relevant to the continuation of human and environmental well-being [33]. The KPI is selected in link to the domain concerned and the motivation of stakeholder. A single pillar indicator can explore one aspect such as “Economy”- sustainability indicator is related to benefit, cost saving, ...; “environment”-sustainability indicator is related to planet, natural resources use, environment management, pollution prevention (water and air quality, energy

conservation and land use); “Society”- sustainability indicator deals with people community, education, equity, social resources, health, quality of life. Moreover, sustainability indicator, not only in a single manner but in a more complex one, can be considered as a quantitative aggregation of many indicators. It can provide a coherent, multidimensional view of a system [2]. For example, energy intensity is seen as one of the important indicators for assessing two pillars of sustainability (economy and environment) [34]. These aggregated indicators are very useful for aiding stakeholders to identify the decision to be taken while supporting specific sustainability interests [4]. Example of such indicators at the system scale is given in Table 1 [33].

Table 1. Proposed KPIs of sustainability for different classified scales and levels of system

Indicator Category	Indicator Types	National Scale Examples	Community Scale Examples
Resource Flow Indicators	<ul style="list-style-type: none"> • Volume • Intensity • Recovery • Impact • Quality 	<ul style="list-style-type: none"> • Greenhouse gas emissions • Material flow volume • Resource depletion rate 	<ul style="list-style-type: none"> • Greenhouse gas emissions • Material flow volume • Water treatment efficacy • Recycling rate • Land use
Value Creation Indicators	<ul style="list-style-type: none"> • Profitability • Economic Output • Income • Capital Investment • Human Development 	<ul style="list-style-type: none"> • Cost (reduction) • Fuel efficiency (gain) • Energy efficiency (gain) 	<ul style="list-style-type: none"> • Cost (reduction) • Fuel efficiency (gain) • Energy efficiency (gain) • Vehicle use (miles per capita)
Adverse Outcome Indicators	<ul style="list-style-type: none"> • Exposure • Risk • Incidence • Impact • Loss • Impairment 	<ul style="list-style-type: none"> • Health impacts of air pollution • Public safety • Life cycle footprint of energy use 	<ul style="list-style-type: none"> • Health impacts of air pollution • Public safety • Sewer overflow frequency
System Condition Indicators	<ul style="list-style-type: none"> • Health • Wealth • Satisfaction • Growth • Dignity • Capacity • Quality of Life 	<ul style="list-style-type: none"> • Air quality • Water quality • Employment • Household income 	<ul style="list-style-type: none"> • Air & water quality • Local employment • Local household income • Housing Density • Infrastructure durability • Community educational equity

These previous KPIs mentioned can be considered as general. Most of the time they should be particularized to be well adapted to the domain, sector for which they have to be used (ex. Finance, business, transport ...). For example, in transport area, annual emissions of CO2, passenger load factor, etc. can be selected as main KPIs of sustainability [35]. More precisely, in industry (thesis context), companies are becoming more and more aware of the environmental and social impact of their actions. Thus, a lot of focused KPIs can be addressed such as use of recycled material, investments in environmental, life cycle footprint, CO2 emissions. This is truer for the manufacturing domain considered as an industrial sector the most concerned with

the TBL requirements [18], [24], [36]. Effectively, sustainability in manufacturing is a very important challenge and especially for Europe [37], [38]. It is one reason of the focus of this thesis in manufacturing.

1.3. To sustainability in manufacturing industry: Green manufacturing

Manufacturing system can be defined as the arrangement and operation of machines, equipment, people, material, people, control and information to produce usable products as required by customers. Manufacturing system can consume different forms of energy input (e.g. electricity, gas) to manufacture several classes of products (e.g. phone, laptop). Manufacturing accounts for more than 30% of the global total energy consumption [37], [38], and it takes a huge accounts for 16% of Europe’s gross domestic product (GDP) and remains a key driver for innovation, productivity, growth and job creation. Manufacturing industry employs more than 32 million people in the EU and contributes about 75% of EU exports. However, manufacturing enterprises are facing with a lot of advanced requirements from environment (new energy resources, climate change, nature disaster), economic (e.g. short product life cycle, new technologies) or social challenges (e.g. high living-standard, training skilled labor).

These requirements are supported by various drivers for sustainability in manufacturing such as customer requirements with environmental regulation, energy crisis or rising trend of energy and material prices. Strategies for Sustainable Industrial Development provided by World Commission on Environment and Development [28] mentioned that “*Resource and environmental considerations must be integrated into the industrial planning and decision-making processes of government and industry. This will allow a steady reduction in the energy and resource content of future growth by increasing the efficiency of resource use, reducing waste, and encouraging resource recovery and recycling*”. So, it is a priority consideration on sustainability for manufacturing plants. More precisely, sustainability in manufacturing means “*the production of products/services in such a way that it utilizes minimum natural resources and produces safer, cleaner and environment-friendly products at an affordable cost or minimize negative environmental impacts while preserving energy and natural resources*” [4]. Sustainability manufacturing enhances the safety of employees, communities and products. For example, Özşahin [39] indicated that a significant positive impact on environmental performance and social performance can be seen by considering sustainability. A schematic structure of the manufacturing in the connection with dimensions of sustainability is shown in Figure 2.

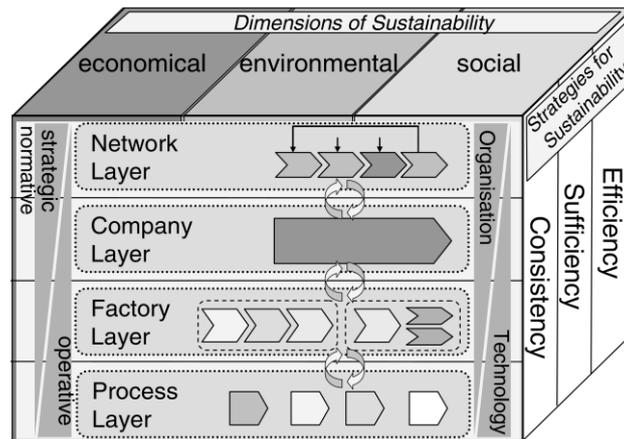


Figure 2. Framework for Sustainable Manufacturing with the three pillars approach [40]

Under the impact of sustainability, EU launched the framework program on Research and Innovation, for 2014-2020, “*the Factories of the Future*” (FoF) program. It is promoting advanced characteristics for the future factories: cleaner, highly performing, environmental friendly, and socially sustainable. Furthermore, “cleaner factory” makes production activities more environmentally friendly by reducing/eliminating wasteful resources (i.e. less raw material, water usage, and energy consumption). In that way, manufacturers respond to the rising trend of demand for clean products/services that meet specific environmental, customer and cost requirements. This advanced vision of manufacturing system takes into account really the TBL together leading to adapt the plant structure, plant digitization, and plant processes. Indeed, the plant structure of the future system has to comprise multidirectional layouts, with a modular line setup and environmentally sustainable production processes (including efficient use of energy and materials), well-interacting together and authorizing flexible production. For example, dynamic arrangement of scheduled working will be more in phase with personal schedule (including interchangeable machines and lines that can be reconfigured). This system evolution promotes the development of manufacturing facilities that are more and more **complex and structured as multi abstraction levels** in the way to make the solution emergent from the interactions of all the components on these levels (e.g. hardware, software, human ...). An example of FoF interacted structure is shown in Figure 3 where a lot of digital technologies are present (e.g. sensors, smart robots, the Internet of Things, big data and analytics). The complexity of this plant is an advantage for being smarter, more adaptable to adjust the process to its real operation conditions and the user needs. In that way, manufacturing stakeholders have high ambitions to enhance their factories —85% of respondents believe they can benefit from implementing elements of the factory of the future [41].

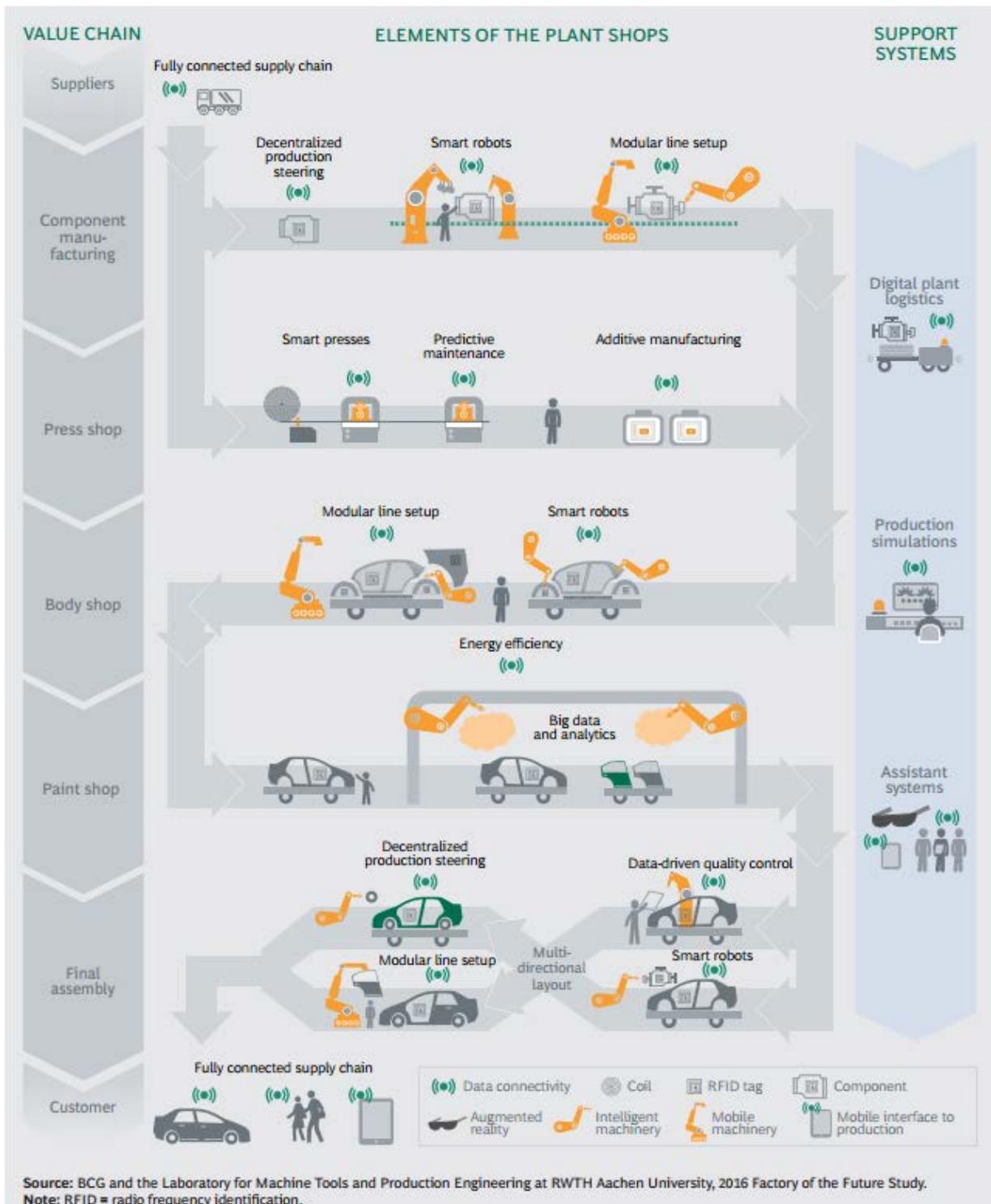


Figure 3. Future manufacturing system with the integration of IT system [41]

This global FoF orientation with regards to the TBL requirements leads to endorse “*Green manufacturing*” or “*Green production*” concept to support “cleaner factory”. “*Green manufacturing*” is defined in several research works [20], [21], such as : “*Green manufacturing is a sustainable approach to the design and engineering activities involved in product*

development and/or system operation to minimize environmental impact”. “A green manufacturing system, which involves reducing energy use, raw materials and solid waste, reusing products, leads to production efficiency (i.e. less energy and water usage) [20]. Thus “Green manufacturing” should avoid harmful waste, reduce hazardous emissions (CO₂), eliminate wasteful resources consumption, model the relationship between energy consumption and other conditions [21].

In link to the previous definition, the KPIs usable in “green manufacturing” (and issued from the list of those selected for industry area) are necessary covering the TBL frame. It can be underlined the following KPIs:

- On environmental performance: air emission, water emission, ... energy utilization, water utilization, ... solid waste, hazardous waste ...
- On economic performance: product reliability, customer compliant ... material cost, setup cost ... on time delivery, cycle-time ... volume flexibility, product flexibility ...
- On social performance: training and development, job satisfaction, ... supplier certification, supplier commitment ...

These KPIs should be calculated at the different abstraction levels (e.g. components, functions ...) of the manufacturing system in accordance with decision-level addressed (operational, tactical, and strategic). Indeed, these KPIs can serve to the different decision-makers (e.g. operator, manager) and all along the system life-cycle, to take optimal decisions in the frame of TBL requirements. This optimality is not easy to obtain because some of sustainability requirements are antagonistic and difficult to be optimized as a whole. In that way, the KPIs are integrated in different decision-making processes representative of all the system life cycle phases (e.g. design, operation). One phase to be focused on is **Maintenance** because it is proven that maintenance can impact and/or cover a lot of sustainable performances within “Green manufacturing” (see Table 2) [42]. Among them, some works underlined [43]–[45], total energy consumption, energy efficiency as key indicators [46].

Table 2. The proposed measures of sustainable maintenance performance measurement systems

Position level	Level 1/ Corporate	Level 2/ Tactical	Level 3/ Functional
Economic Performance Measures			
Cost effectiveness perspective	Return on eco-friendly maintenance investment and innovation Computerized maintenance management system Manufacturing budget Maintenance budget	Production cost/ unit Preventive maintenance cost Corrective maintenance cost	Direct material Direct maintenance labor Overhead cost Direct material Direct maintenance labor Overhead cost
Quality perspective	Maintenance cost/ unit Overall plant effectiveness	Overall department effectiveness	Overall equipment effectiveness Availability Performance rate Quality rate Mean time between failures Number of breakdown
Productivity perspective	Maintenance efficiency	Preventive maintenance task Corrective maintenance task	Maintenance program achievement Quality for maintenance task (rework) Response time for maintenance Start up after shutdown Mean time to repair
Environmental Performance Measures			
Environmental perspective	Resources saving Environmental illegal cases	Total of spare parts used Total of lubricants consumption Total of water consumption Total of land used Total of energy consumption Water pollution Land contamination Air pollution	Original spare parts used Recycled spare parts used Re-purposed spare parts used Remanufactured spare parts used Original oils consumption Synthetic oils consumption Vegetable oils consumption Fresh water consumption Recycled water consumption Non-renewable energy consumption Renewable energy consumption Total of bio-degradable components used Total of bio-degradable lubricants consumption Total of bio-degradable cleanser consumption Total of hazardous waste Total of greenhouse gas emission
Social Performance Measures			
Learning and growth perspective	Skill improvement related to sustainable maintenance practices Number of innovation carried out related to sustainable maintenance	Training topics Innovation suggested	Training hours per employee Small group meetings/ team work
Health and safety perspective	Lost time injury rate Health and safety illegal cases	Recordable injury rate Physical working environment	Safety attitude Toxic spare parts Toxic lubricants Toxic cleanser Workplace noise level Lighting and ventilation
Employee satisfaction perspective	Employee turn-over rate	Employee satisfaction rate	Employee complaints
Stakeholders satisfaction perspective	Stakeholders - company partnership in terms of sustainable maintenance practice	Stakeholders satisfaction rate	Stakeholders complaints

In fact, energy (in general) is as an important input for a system to produce external activity or perform work required by any industrial process [47]. Energy usage is linked to social development, economic development, environmental pollution and climate change. For example, the energy cost for the total life-cycle of one industrial component can transcend capital investment. In the case of an electrical motor, among the 100% total life-cycle cost, 2.5 % is

related to the purchase cost, 1.5 % is for maintenance and 96 % is the cost of energy used [48]. It leads to consider energy and its derivate materialization in terms of **energy consumption** and **product manufactured (useful output)** as a main sustainability KPIs in manufacturing [39] and more precisely “Green manufacturing”. Moreover, the ratio between energy consumption and useful output can be represented with an **Energy Efficiency value (EE)**. EE provides substantial benefits in addition to energy cost savings, profitability, production and product quality, and improving the working environment while also reducing costs for operation and maintenance, and for environmental compliance [49], [50]. For example, EU established motivated targets towards industry: a 20% energy savings target by 2020 and moving towards a 20% increase in Energy Efficiency. Thus EE seems an important target for sustainability in manufacturing and more precisely with regards to maintenance decision-making process.

1.4. What is energy efficiency in general ... and then in industry?

1.4.1. Energy efficiency in general

EE is an universal concept mentioned in various applications and known under various names like energy intensity [51], [52], specific energy consumption [53]–[55], energy conservation [56]. Indeed, the definition of energy efficiency is a complex issue. Generally, energy efficiency means more concretely that a smaller amount of energy input is needed for the same useful produced output/services, or that a higher output/services may be provided with the same energy input. For example, single crystalline photovoltaic panel can produce more electrical energy than thin-film photovoltaic panel with the same incident solar power. So saving energy or reduction of energy consumption are well-known behaviors of EE such as replace incandescent bulbs by florescent lamp.

The relationship of EE with economic, social behaviors or environmental issues have been already analyzed over the past decades [57], [58]. It is due to the interests to be **energy-efficiency** with increase in demand for energy, rising energy, materials prices, changing consuming behavior of customers to be green ... together with the growing environmental concerns. There are many benefits of using energy efficiency, as illustrated in Figure 4.

The benefits/interest in EE is also related to the energy consideration level. For example, the top manager often considers carbon level (annual CO₂ emission), annual energy consumption, annual energy cost and performance of EE policies. The operator, on the other hand, is concerned

about daily/weekly energy consumption, power factors or power quality events (e.g. power supply interruptions).

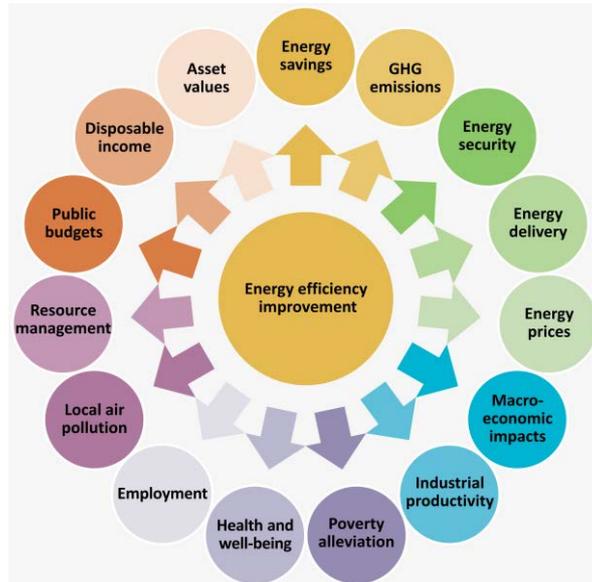


Figure 4. Multiple benefits of energy efficiency [59]

To support these benefits, EE is achieved by high technology, improving people awareness etc. They are founded in the theoretical frameworks on energy efficiency (codes, standards, label, guideline, the best energy efficiency solution handbooks, etc.) and supported by different laboratories, international organizations and governments [47], [57], [60].

1.4.2. Energy efficiency in industry and mainly in manufacturing

From these frameworks, declinations for EE can be done in link to different sectors such as industry. Indeed, industry takes a major proportion of primary energy consumption, and can have a huge potential in saving energy consumption by improving EE. For example, the EU's industrial sector plays a central role for 26% of European final energy consumption. Energy efficiency in EU manufacturing industries has improved on average by 1.3% per annum over the last 15 years (reducing final energy use by 15% in aggregate since 2000). The potential additional savings with a 2030-2050 horizon are substantial [61].

To face this saving, EE studies cover different sizes of industrial plants: from larger enterprises to small enterprises, from complete plant level to component/end-user level. For example, consideration of energy efficiency in plant management [55], [62] can be practically observed in the automobile industry [51], [63], [64] to reduce fuel consumption and environmental loads by deploying the product life-cycle, or in the paper industry [52], [64] to save the use of traditional energy, and to take more advantage of renewable energy [65]–[67].

Thus, the energy efficiency understanding can vary with industrial domain and type of used energy [22], [23]. It leads to consider EE under different forms like thermal energy efficiency [68], economic ratios, techno-economic ratios [69], energy intensity or energy efficiency intensity [70], [71], Energy Efficiency Design Index [72], or benchmarks for energy efficiency [73], fuel economy [74], [75]...

These EE forms for which understanding of EE properties is increasingly important [50], are also considered in manufacturing domain because EE is shown as a way to increase the competitiveness of manufacturing system [51], [69], [76]. It is illustrated in the sustainable manufacturing framework given in Figure 5 [62] for contributing to the TBL. Indeed, during recent years, energy consumption of manufacturing industry domain has achieved a rapid growth. International Energy Agency (IEA) presented in energy efficiency market report that over 23 % of global energy consumption is consumed by manufacturing industry [38], [75]. It takes the second place in the energy and emission by end users according to the same IEA’s report. Moreover, manufacturing is continuously expanding with huge investment and rapidly increase in facilities to supply the demand of good/services for modern life [77]. It leads to integrate EE in the Energy Management System (EMS), which was recently implemented, to help managers master their system [78], [79]. EMSs with energy monitoring systems (online/offline, continuous or energy audit, etc.) have been proposed and successfully been applied in different types of manufacturing system [80]–[82]. In that way, optimization of EE in manufacturing with regards to the other KPIs is appearing as a main challenge for decision-makers.

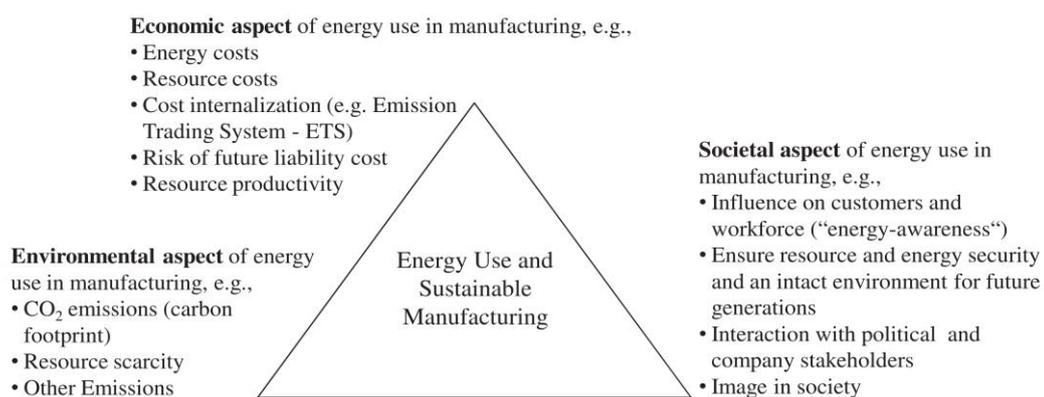


Figure 5. EE contributing to TBL of sustainable manufacturing frameworks [62]

Nevertheless, few works already exist on EE in decision-making process. For example, Trianni [83] studied the benefit of EE in both decision-makers and policy-makers. In fact,

industrial system such as manufacturing one has to face with a set of stakeholders, including decision-makers, energy providers, end-users and operators interacting at different layers according to their roles, and in consist with the decision/action levels to be addressed (e.g. operational, tactical or strategic levels) [71], [84], [85]. At the operational level, the issue should be: How the energy consumption and thus the energy efficiency of machines and production systems have to be materialized to give the right decision as soon as possible (nearly real time) [85]? In another way, at higher level (tactical or strategic levels) only energy consumption is used to modify the usage of different types of energy resources.

Whatever the level addressed, the EE is mainly assessed by a value. It is represented by the **EE Indicator, named EEI**, as an index for evaluating the energy efficiency at a specific time. However, no generic formulation of this indicator is available today in the manufacturing field to be applicable to the different abstraction levels. Indeed, even if some methods to assess EEI exist, they are addressing principally EEI values at the component level without considering really it at the system one which can be better for performance optimization [5], [6]. Moreover, this assessment is not easy to do because it should take into account the dynamics of the system (age, degradation, different loading profiles, etc.) impacting the EEI value and leading to track its evolution in the future to clearly define the **Energy Efficiency Performance (EEP)**. The EE Performance is a performance materializing if the industrial system is efficient or not (it is more than a value; it is the value in time). However, today, most of the studies on EEP considers that EEP (through EEI) is time-independent [86], [87]. Predicting the degradation behavior of energy efficiency of components/systems is therefore crucial [88], [89] in order to anticipate the increase in global energy consumption, improve opportunities to save energy, etc. So, the consistent formulation of these EEI and EEP items is not evident [7] especially with regards to dynamic context (dynamics of the systems) for predicting the EE evolution in the same way as it was done through the use of conventional prognostics approaches to predict the Remaining Useful Life (RUL) of components/systems [8]–[11].

Thus, in summary with the EEI/EEP consideration in green manufacturing, the first important challenge addressed in the thesis is:

How to define and evaluate/predict EEI/EEP at the different abstraction levels of an industrial (manufacturing) system by considering the dynamics of this system? - Challenges No.1

The results of these formalizations should be integrated in the decision making processes of the manufacturing system to master the EEI/EEP as close as possible to its nominal value for controlling Environmental Pillar. More precisely this mastering requirement can be supported by the maintenance decision-making process as advocated the Prognostics and Health Management (PHM) community [12]–[14]. Indeed, an efficient maintenance strategy could not only avoid the failure of the system but also allow to anticipate the growing up of global energy consumption. Nevertheless, the current maintenance decisions are mainly based on conventional indicators such as reliability, availability, direct cost, etc. [15] and only just some investigations have been realized to consider the relationships between EEI and maintenance strategy [16], [17]. For example, Xu and Cao [16] addressed the average energy efficiency under periodic maintenance as a criterial criteria for the maintenance decision making process at machine level only.

This relationship between conventional indicators and sustainable ones for maintenance opens up a new path to define/adapt the “condition” to trigger the maintenance (CBM one) according to sustainability requirements and the evolution of their values (to promote originality towards EEP).

1.5. How to integrate EEI/EEP in maintenance decision-making and more precisely in CBM?

Maintenance is defined as “combination of all technical, administrative and managerial actions during the life cycle of an item (e.g. component, machine) intended to retain it in, or restore it to, a state in which it can perform the required function” [90]. This combination leads to support different strategies depending if the item is already failed (corrective strategies) or not (preventive strategies) [91], [92]. However, the question of how EE helps or impacts these strategies is only in investigation.

1.5.1. Classification of maintenance strategies

Maintenance strategies are implemented with regards to strategic decision (after or before failure) and by organizing all the activities to support this decision execution (e.g. management, planning). So, maintenance strategies have been chosen either on the basis of longtime experience or by following the recommendations of manuals provided by manufacturers [93] such as original equipment manufacturer (OEM) recommendations. There are classified, as

presented in Figure 6. in two main categories: corrective maintenance and preventive maintenance [90], [94]–[96].

Corrective maintenance: It includes all the maintenance activities that are carried out after fault recognition and intended to put an item into a state in which it can perform a required function [97], [98]. For example, corrective action is necessary when the system is failed but could be investigated when the component is not critical both on the **direct** and **indirect** costs (e.g. low cost components) [45]. In some other cases, when the indirect cost is high, corrective maintenance should be avoided as much as possible.

Indeed, costs can be classified as direct costs and indirect costs based in the way they contributed to the objective of manufacturing system [45]. The direct costs are directly related to all the “resources” needed to develop the maintenance actions. Indirect costs are more the costs concerned by the impacts of the fact that the system is stopped (for developing the maintenance action for example after corrective situation) or that the maintenance action is not done keeping the system as degraded (non-optimal performance situation).

Corrective maintenance can be declined in palliative maintenance (e.g. Maintenance action to recover a part of the performances as it was before the failure) or in curative maintenance (e.g. change the failed component to be As Good As New after the action).

Preventive maintenance: Maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce/prevent or delay the probability of failure or the degradation of the functioning of an item (reducing the number and cost of failure of an item, increasing system reliability, improving availability equipment, ensure the security of individuals and the environment, facilitate inventory management, etc.) [97]–[99]. Preventive maintenance makes sure that maintenance is performed before failure occurs to avoid corrective maintenance actions. Preventive maintenance may be either scheduled maintenance, predetermined maintenance or condition based maintenance (CBM).

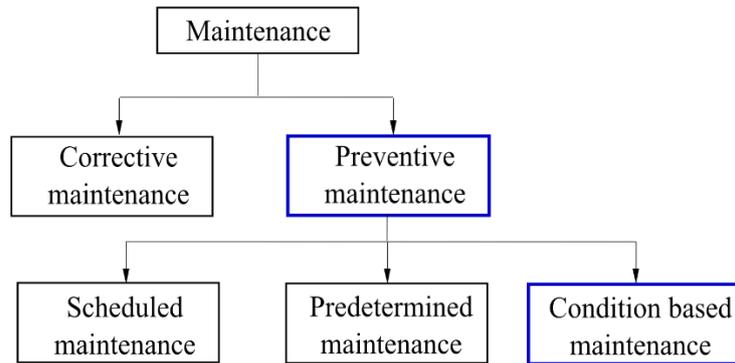


Figure 6: Simplified classification of maintenance strategies

Scheduled maintenance (Time-based or planned maintenance): Preventive maintenance which is carried out in accordance with an established time schedule or established number of units of use. It leads to develop potentially actions too “soon” or too “late”.

Predetermined maintenance (Age-based maintenance): Preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation. Substantial remaining useful life is wasted if the machine is still in reasonable condition when preventive maintenance is performed, and a breakdown might occur if it happens to deteriorate faster than expected [100].

Condition Based Maintenance (CBM): Preventive maintenance which is based on performance and/or parameter monitoring and the subsequent actions. The monitoring of performance and parameter, called “**condition**”, may be scheduled, on request or continuous (e.g. real time monitoring). Thus, it includes a combination of condition monitoring and/or inspection and/or testing, analysis and the ensuing maintenance actions. An extension of CBM is called Predictive Maintenance which is corresponding to a CBM carried out following a forecast derived from the analysis and evaluation of the significant parameters of the degradation of the item. CBM also considers external, random failures (for example, shock, natural disasters, humans mistakes) [101].

The principle of CBM is therefore to perform maintenance action by anticipating causes before the failure occurs in order to avoid the effects of unexpected failures. The anticipation is related to the tracking of **degradation level** of the condition (degradation indicator). As the condition can be parameter or performance, the tracking of this degradation can be directly on a raw signal, an information (resulting from signal processing), an indicator (resulting from information fusion), a health state (resulting from indicator fusion) as advocated by PHM

community ... The indicator has to be compared to a threshold representing the limit of the value considered as acceptable. Then, this degradation indicator is used as input of the **maintenance decision-making process**. In that way, CBM is really examined by industry to be more **just in time** in maintenance. For example, the vibration and temperature of the mechanical component such as bearings and gears or the current and voltage provide the “condition” of an electric motor [94]. Deterioration process due to tear of belt-driven system [102], [103], wear of cutting [104], [105], crack of rolling part [106], [107] may be selected as “deterioration” condition for CBM. Hazards could be also considered as a condition for CBM strategy [108].

Through this notion of “condition”, CBM seems the best strategy to be investigated to trigger the maintenance action according to sustainability requirements and the evolution of their values (in terms of degradation impact; EEI then EEP). The value is going up to the threshold. Indeed, tracking a conventional indicator or a sustainable one could use the same techniques and brings similar advantages.

In terms of advantages, the CBM, implemented through different ICT products (e.g. sensors, networks, software ...) can extend equipment life (age), reduce risk and improve the efficiency of equipment [109]. CBM can also indirectly contribute to optimisation of the production process (e.g. better mastering of product quality) [95], minimizing costs of maintenance [45].

The general decision-making process for CBM deployment is synthesized in Figure 7. It is consistent with standards to help engineer for developing particular CBM platform/architecture related to the system to be maintained. The main well-known standard is the OSA-CBM (Open Systems Architecture for Condition-Based Maintenance) [45], [110]. The OSA-CBM architecture is structured on 6 processes to carry out the action from the data acquired: Data Acquisition, Data Manipulation, State Detection, Health Assessment, Prognostics Assessment and Advisory Generation.

More precisely, by taking into account the result of the health assessment process in terms of advanced information about the system operation (including production plans, logistics schedule, resources available ...), the prognosis allows to track the future state of the system [111]. It is more true now in the more recent CBM studies [112]–[114] while considering not only condition at current time but also in the realistic operating conditions of the system over time (in the future).

However, the main issue on CBM is related to the identification of the most suitable “condition” (indicator) and how to master/evaluate this indicator to use it as input of the decision-making process (with regards to the threshold fixed). Indeed, the methods/tools to select and support “condition” indicator evaluation, and threshold fixing are not completely available. It is necessary to find methodologies usable with regards to the complexity of the system targeted, its main properties to be monitored (e.g. performances, parameters) and to the decisions to be taken in an optimal way. More precisely, optimal maintenance decisions for a complex system are not necessarily obtained by the superposition of individual decisions found at each level of the system.

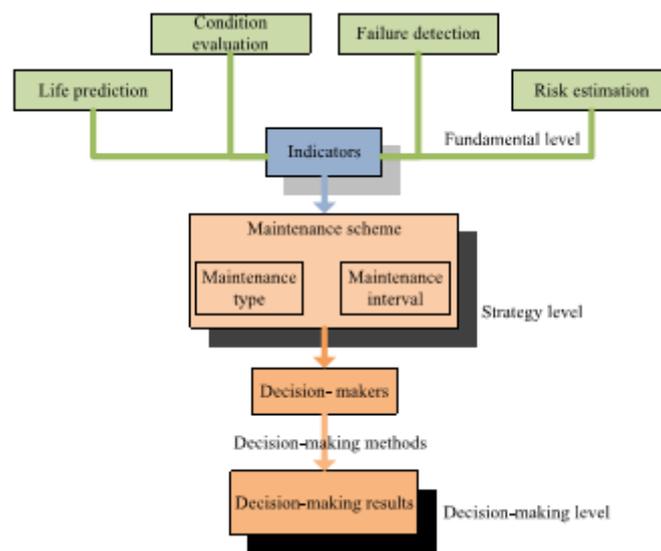


Figure 7. Structure of CBM decision-making [109]

This superposition in the decision is all the truer by considering both types of indicators, conventional and sustainable one such as EEI/EEP. Sustainability consideration in CBM means for example: When an item (component/system) consumes more energy, it should be replaced even if it is not degraded with regards to other properties such as wear. In that way, maintenance of the component could be realized to preserve its energy property [87], [115]. It is an original way for developing maintenance.

1.5.2. Is Energy Efficiency already integrated in maintenance and mainly CBM?

Only few works on the impact of maintenance on the EEI/EEP (mostly amount of energy saving or energy consumption) already exist in industrial area. For example, Yildirim and Nezami [116] studied energy consumption model under the impact of minimal repair and potential recovered EE after implementing maintenance as computed by using efficiency curve.

The developed cost model shown that better cost benefits can be achieved by considering the energy consumption of production process to decide the maintenance actions. These benefits can be results of a low energy inspection cost (by investment in energy monitoring system) or the balance between maintenance cost and energy cost. Mora et al. [7] mentioned EE as a trigger of preventive maintenance actions, and take into account energy cost in comparison with the preventive maintenance cost for maintenance decision making process. These previous works are mainly related to scheduled or predetermined maintenance strategies. Indeed, CBM strategies are not really addressing EE properties. EE is seen only as the auxiliary result of these previous CBM plans. For example, Sánchez and Goti [117], [118] investigate the preventive maintenance scheduling problem in a production system where maintenance is impacting the production speed and quality. They show production speed and output quality decrease as a function of machine deterioration [119] and optimized energy consumption can be reflected in many maintenance schedules. The impact of maintenance and operating procedures (at function/system level) into energy model to calculate energy consumption is addressed, then energy saving is the objective of maintenance plan instead of conventional indicators for maintenance decision making process [17]. Optimization framework can provide enhanced decision support leading to optimal operation and maintenance [120]. Nevertheless, these works are not really developed by integrating EEI/EEP as concrete conditions to be tracked for aiding the maintenance decision process. It leads to identify the second important challenge addressed in the thesis which is:

How to use EE into CBM strategies? - Challenges No.2

This challenge placed the main originality of the thesis by considering EEI/EEP as conditions to trigger suitable maintenance action, which allows not only to avoid the failure of the industrial component/system but also to maintain the EEI/EEP. In that sense, the degradation indicator in the thesis is considered as a quantified indicator directly related to the state of degradation or performance of an item (component, machine, system) from which it is possible to detect a failure.

1.6. Conclusions

This chapter presented the sustainability context of this thesis. It is more focused on sustainability in “Green Manufacturing” by considering the requirements of some initiatives such as FoF (advanced manufacturing) in which it is advocated “cleaner factory” as a necessary

way for the future generation. Among the KPIs representative of the TBL of this factory type, Energy Efficiency (EE) was identified as the main important one. It allowed to underline EE Indicator (EE value at t time) and EE Performance (evolution of the EE value in time according to dynamics of the system) as two items must be necessarily mastered at each level of the manufacturing system to gain the green property.

The results of this mastering should be integrated in the maintenance decision-making process (mainly CBM one) of the manufacturing system to control the EEI/EEP as close as possible on its nominal value. Nevertheless, current maintenance strategies are not well adapted to support this integration because mainly based on conventional indicators and not sustainable ones.

Therefore, with regards to the two conclusions on EEI/EEP mastering and its integration in maintenance/CBM strategy, the chapter highlighted two main challenges to be addressed in the thesis:

- ***How to define and evaluate/predict EEI/EEP at the different abstraction levels of an industrial (manufacturing) system by considering the dynamics of this system?***
- ***How to use EE in CBM strategies?***

These two challenges serve in chapter 2 to define the scientific issues to be attacked.

Chapter 2

Scientific problem statement on EE concept and its application in CBM maintenance decision-making

2.1 Introduction

The chapter 2 aims to define the scientific issues which are related to the two identified industrial challenges of chapter 1. In that way, the chapter 2 starts from challenge 1 with the consideration of using EE in general in order to underline the categories to develop EEI concept at multi-levels of a manufacturing system. Then it is investigated generic EEI formulation taking into account the common characteristics of manufacturing system (complex, multi-level structure, dynamic context). From this EEI formulation, the time-dependent factors are considered to track EEI evolution to introduce EEP. It allows to focus on EEP as the estimation of the residual life energy at different levels of manufacturing system. After that, the dynamics of the system and its relationship with prognostic are investigated. It enables to isolate the interest of a generic approach to predict EEI evolution and estimate EEP by applying suitable prognostics. Finally, with regard to challenge 2, an investigation is done about innovation on maintenance decision-making (focus on CBM) by trigger maintenance actions not only by using conventional conditions but also EEI/EEP ones.

2.2 How to define and evaluate/predict EEI/EEP at the different abstraction levels of an industrial (manufacturing) system by considering the dynamics of this system?

In link to the first challenge defined in chapter 1, it is important to focus first on EEI concept (see section 2.2.1), then its consideration at multi-levels of a manufacturing system (see section 2.2.2), and finally on the EEP concept (see section 2.2.3) as an aspect of EEI evolution with the consideration of the system dynamics (see section 2.2.4).

2.2.1 General concepts of EEI and their application in manufacturing systems

Over the past decades, many governments and industrialists have focused on energy efficiency (EE) assessment as a powerful tool for decision-making. Indeed, this assessment should lead to strategic decisions and priority actions for reducing energy consumption, energy demand and environmental problems. For this assessment, EE is generally expressed as using

less energy to produce the same amount of services or useful outputs. In that way, EE equation is most of the time formulated as: $\frac{\text{Useful output of a process}}{\text{Energy input into a process}}$ [121]. It means that a smaller amount of energy input is needed for the same useful produced output, or that a higher output is provided with the same energy input. In this way, energy efficiency can be used in a very wide range of applications and for different levels of features [122] in terms of energy demand sectors (e.g. buildings, appliances, transports, industries, services, etc.), sizes (e.g. on a local, national, international or global scopes), stakeholders (e.g. decision-makers, energy providers, end-users, energy services companies, energy audit services companies, or particular equipment). For example, EE has already been investigated in several sectors such as industries [51], [64], transport [63], [123], and buildings [124], [125]. Nevertheless, for each sector [55], [87], different visions of EEI concept have been introduced but it is globally accepted that these visions belong to four categories to design EEI [57], [126].

1- Thermodynamic indicators: They are measured as the energy dissipated or consumed by the system compared to the amount of energy in the resource processed. Both input and output are measured in thermodynamic units (e.g., GJ (Gigajoules) of delivered energy consumed in the production coke for coking coal). The importance of efficiency comes from the thermodynamic laws, namely the conservation of energy and the irreversible energy conversion to uselessness. By decreasing the energy loss in the processing, the useful energy transformed from energy input is increased. Thus, the thermodynamic definition of energy efficiency can be expressed as follows: $\frac{\text{Useful work or energy output}}{\text{Energy input}}$ [127]. Based on this definition, this type of indicators should not be applied to unknown thermodynamic characteristics or to the case in which there is no or poorly-monitored process because of missing information about energy loss. Relatively, thermodynamic indicators are not the best choice at the top level of national and international energy. Indeed, using this type of EEI, energy efficiency presents changing trend (improvements/decrements) of several energy conversion facilities. It can be underlined such as the promising conversion efficiencies to convert sunlight into electricity energy. It can reach to maximum 44.3% of conversion and depend on the types of PV panel [128]. According to [129], thermodynamic energy efficiency can be used only at the device level, end-use technology or energy conversion technology.

2- Physical-thermodynamic indicators: This kind of indicators has been introduced to avoid the limit of thermodynamic indicators in systems with output units that are

uncountable or specific energy format like systems in transport or agriculture. In fact, the output is evaluated in physical units while the input is in energy. In this way, the energy efficiency can be evaluated as follows: $\frac{\text{Useful physical output}}{\text{Energy input}}$ level [126], [130], [131]. It is important to note that the units of physical output have to be expressed in the designed units of the system capacity (tons of cement, passengers, kilometers, vehicles, the number of rooms, etc.). Calculated in either aggregated or disaggregated methods, these indicators directly stick to the technical power flow. As a consequence of various physical outputs, multiple forms are used for physical-based indicators such as energy intensities, specific energy consumption, etc. In spite of difficulties in quantifying the higher level of aggregated process, the physical-thermodynamic indicators can be applied to a variety of levels ranging from a very simple component level to a sector level [132].

3- Economic-thermodynamic indicators: These indicators are hybrid indicators, in which the energy input is measured in thermodynamic units and the output is measured in market prices (\$). The market prices are measured by the GDP or the market value of all final goods and services produced within a country or a sector [121], [131]. In this case, any difference in the output or input number can be affiliated to economic, social behaviors or calculation methods. The information of technical process is unnecessary and the energy output number is conveyed through energy price factors. The “Energy:GDP” increments may be misunderstood as the positive result of energy efficiency investment. But economic-thermodynamic indicators can be calculated by multiplying thermodynamic indicators with the economic value of output units. Thus, these indicators can be applied to high levels of economic structures such as the corporate, sub-sector, sector and national levels.

4- Economic indicators or monetary indicators: These indicators are used to measure changes in energy efficiency purely in terms of market values. They are named as the energy to GDP ratio, energy coefficient or energy elasticity. Economic indicators are given as the ratio of energy consumption in an energy unit to an economic activity in a monetary unit $\frac{\text{Dollarized of output}}{\text{Dollarized of input}}$ [47], [48]. Sometime, these indicators are convertible from their physical-thermodynamic indicator counterparts by simply multiplying the energy input with appropriated added energy prices. But, in another way, these economic indicators are just seen as a purely economic efficiency indicator rather than as an EEI because they are fully measured in economic values. This type of indicators should not be used in monitoring

energy efficiency performance systems. The economic indicators are often used when energy efficiency is measured at a high level of aggregation (international, national and sector levels), where it is impossible to characterize the output by a single physical unit.

In conclusion, some of these categories of EEI are limited to the physical evaluation of energy transformations, while others also consider the economic and social dimensions that define the usefulness of a process [133]. The consideration of these dimensions for EEI is mandatory in the frame of TBL as advocated by Manufacturing system and more precisely “Green manufacturing”.

Indeed, as already explained in chapter 1, the manufacturing system under the orientation of FoF (more “cleaner factory” property) is mainly characterized by:

- (i) The energy consumed which can be represented by different forms (e.g. electricity, gas, oil),
- (ii) The outputs produced which can be materialized by different products or classes of products due to the flexibility/adaptability of the system (e.g. a same assembly line can assemble different parts to form different final products),
- (iii) The structure which is complex and organized on multi abstraction levels.

Thus, these characteristics have to be taken into account to select which one of the EEI categories is the most adapted to manufacturing system. In that way, the next table is showing the main advantages and disadvantages about the use of these categories in manufacturing system [69].

Table 3. The advantages and disadvantages of the categories of EEI to be applied in manufacturing systems [69]

	Primary Advantages	Primary Disadvantages
Thermodynamic Energy Efficiency $= \frac{\text{Useful work or energy output}}{\text{Energy Input}}$	<ul style="list-style-type: none"> - Different forms of energy inputs is converted to common form. 	<ul style="list-style-type: none"> - Hidden energy in output is not the most concern of manufacturing system. - Thermodynamic laws are not easy to use for calculating the energy losses for all machines/component of manufacturing system.
Physical-Thermodynamic Energy Efficiency $= \frac{\text{Useful (Physical) Output}}{\text{Energy Input}}$	<ul style="list-style-type: none"> - Physical measures for the output(s) can be determined and mastered during manufacturing process. - EEI can be defined individually for multiple functions (with different outputs) within the same manufacturing system. 	<ul style="list-style-type: none"> - Difficulty to evaluate the energy input allocated for different types of outputs.
Economic-Thermodynamic Energy Efficiency $= \frac{\text{Dollarized Output}}{\text{Energy Input}}$	<ul style="list-style-type: none"> - The aggregation of several forms of manufactured outputs can be calculated by assigning market prices. 	<ul style="list-style-type: none"> - EEI is influenced by other economic factors. - The changing of EEI value is not representative of the system structure modification and without possibility to locate the technical causes of EEI changing.
Economic-Economic Energy Productivity $= \frac{\text{Dollarized Output}}{\text{Dollarized Energy Input}}$	<ul style="list-style-type: none"> - EEI of different manufacturing systems can be compared and aggregated at various levels. 	<ul style="list-style-type: none"> - EEI is influenced by other economic factors. - The changing of EEI value is not representative of the system structure modification and without possibility to locate the technical causes of EEI changing.

This previous positioning about the four EEI categories with regards to manufacturing system underlines that any specific category is supporting the main characteristics defined for this type

of system [68]. So, a first scientific need is to clearly **define the EEI in the context of manufacturing system and more precisely “Green manufacturing” as defended by FoF initiative.**

2.2.2 EEI at each level of abstraction (component, function/system) of a manufacturing system

This scientific need is all the truer since the EEI formulation to be found must be applicable to the **different abstractions level of a manufacturing system** (the third characteristics mentioned previously).

Indeed, such system has to be faced with a set of stakeholders, including decision-makers, energy providers, end-users and operators [71], [84] interacting at different abstraction levels according to their roles, and in consistency with the decision/action levels to be addressed (e.g. operational, tactical or strategic levels). Moreover, this level consideration implies also to retrieve data on energy consumption (e.g. kWh, Btu, ton of coal) and output unit (e.g. amount of manufactured cars) consumed and produced at each level, knowing that there is often limited resources (financial, labor, instrument, etc.) for collecting this necessary data. Thus, one challenge is to found, in an optimal way, what is the EEI the most applicable at each level by considering also the retrieval of the data. In relation to this challenge, the Table 4 is providing a first illustration on the relationships between EEI and application level in manufacturing area in order to give to the decision-maker some helps for selecting the best EEI [1].

This table highlights the potential availability of EEI at each level of manufacturing system (and its enterprise context). Nevertheless, these EEI are positioned in an isolated way (each one is issued from a specific work) without introducing rules for developing one EEI at a specific level from EEI at another lower level (e.g. aggregation principle). Indeed, for example, some existing works focus on EEI at component level (i.e. operational layer) [134]–[136] without considering it at higher level (i.e. the strategic layer) which may be useful even essential for optimizing decision-making process [137], [138].

Table 4. Consideration of EE concepts at different levels of manufacturing

Reference	EE indicator	Level of application in manufacturing area
[16]	Energy consumption Physical-thermodynamic indicators	Component/equipment
[25]	Energy efficiency label	Factory level Department level Unit process level
[57]	Physical-thermodynamic indicators Thermodynamic indicators	All levels of manufacturing process
[62]	KPIs Benchmarks	Country level Sector level Plant level
[120]	Energy consumption	Function/system level
[139]	Thermodynamic indicators Physical-thermodynamic indicators	All levels of manufacturing system
	Economic-Thermodynamic indicators	Factory level Sub-sector/sector level Industrial sector level Country level
[140]	Physical-thermodynamic indicators	Function/system level
[141]	Physical-thermodynamic indicators	Machine level

According to this separation highlighting (component/system), most of the time the EEI at component level, is based only on the measurement of its energy consumption and its output with the consideration of several impact factors/features associated with individual components like temperature, voltages and harmonics. **Thus, EEI value at this component level can be directly measured.** For example for an electrical motor, its EEI is based on the energy consumption and produced mechanical energy taking into account several parameters (e.g. speed, frequency of harmonics) [142]–[144].

At the system level, EEI should be representative not only of the components which are inside this system (different components place in series and/or parallel) but also of the global behavior of this system which is resulting from the components interactions and the operational conditions. This global behavior can be impacted by the service of the system which is depending of the outputs to be delivered (e.g. a same system can support different services in link to its adaptability/flexibility level). So, the EEI assessment at this level is not easy to do due to this dynamic consideration impacting necessary energy consumption characteristics[145]. About

system level, Behrendt [146] argued that the largest energy efficiency potential belongs to the higher system levels. He developed an EEI model based on the three levels of industrial electric motor-driven system, including operational conditions and human aspects. This model is comprising the components behaviors, the interactions between them, but also the behavior of the whole system regarding to the service to be achieved.

Thus, the interactions between the components identified by their own EEI, in the way to deliver the EEI at the system level have to be clearly understood. It is materializing the required step from component/system separation to component/system integration. Indeed, both energy consumption and output (the two main properties of EEI) at component level should be used to calculate EEI at function/system level. However, these interactions are representative of a **complexity** not so easy to understand. For example, the energy consumed by a component may be transformed to energy to be consumed by another one ... with some energy loss due to the transformation (e.g. air compressor transforms electricity to air pressure for another component). The same situation exists with output of one component, which may be reused as input of other component. Through these transformations and the resulting losses, it becomes clear that the **energy consumption model at system level** (suitable to provide the basis for the energy optimal use of manufacturing plants) cannot be based only on the sum of the individual components [147], [148] but must integrate the energy consequences of the component interactions.

In addition, EEI assessment both at component and/or system levels needs also to consider some **factors** which are impacting their properties (energy consumption and output) [148] [149]. Indeed, EEI is influenced by several factors such as the system age/degradation, the type of energy resources (coal, fuel, electricity), the technology employed for controlling EE [150] ... These factors are representative both of **internal parameters** or events to the component/system (e.g. machine speed, energetic profile) [141], but also **external parameters** or events to the component/system (e.g. system context). These factors could be also different in relation to the different abstraction level addressed (in link to decision to be taken) [25]. It means that these impacts have to be modelled with regards to EE consequences by taking into account the external and internal considerations. It requires a more detailed analysis of the component/system to be able to identify these impact factors.

A part of this analysis has to focus more precisely on the identification of other KPIs which can influence the EEI. Indeed, EEI can have cause-effect relationships with other performance indicators (mainly those coming from maintenance area). For example, a positive evolution on

KPI related to productivity leads generally to an increase in energy consumption at manufacturing system level. So, the increasing trend of energy consumption cannot be fully representative of EEI of the manufacturing system (EEI value is not only in line with energy consumption) [151]–[153]. In another way, to reduce energy cost, work initially scheduled can be moved to low-tariff energy prices shift (the low energy price is normally fixed during the night) which can impact the workers attitude due to the night context [154]. This attitude change can lead to a waste increasing (including material and energy), the later directly negatively impact the EEI.

In summary, with regards to the statement developed in section 2.2.1 and section 2.2.2, problems have been underlined in link to the definition of EEI at different abstraction levels of a manufacturing system by considering interaction between these EEIs but also impact factors.

This report can be reinforced, in industry area, by the gaps identified by [155]–[157] and summarized in Table 5 [158].

Table 5. The research gaps and industrial needs addressed in industrial system

Gap description	Industry Need	Degree of GAP Satisfaction	How the study addresses the gap
<u>GAP 1</u> Only few of the state-of-the-art energy-related indicators are suitable for energy management applications within a manufacturing plant	More direct focus for supporting energy management at plant level: Energy-related KPIs at machine, process and plant level	● Decisive Contribution	Development of energy-related KPIs at machine level. Application of the method is currently dedicated to machine tools and machining centers. The method can be extended to more aggregate levels
<u>GAP 2</u> Benchmarking of energy efficiency between manufacturing plants is difficult and not always applicable	Benchmarking-oriented plant level KPIs which can compare energy efficiency of different plants and processes that are similar in terms of features of production	○ Marginal Contribution	The analysis of the cause-effect relationship between energy consumption and manufacturing system shows the existence of a large number of variables that affect energy consumption. The proposed e-KPIs offer ample possibilities for use in benchmarking applications considering the different variables of energy consumption
<u>GAP 3</u> Indicators do not report any information about how energy is used in a manufacturing plant Technological monitoring limits exist	Energy-related KPIs which identify inefficiencies at plant level	● Decisive Contribution	The purpose, with which the energy-related KPIs are developed, is to provide an analysis tool that can be easily used by management to identify inefficiencies and areas for improvement with the aim of continuous improvement
	Using real time, high granular information of energy consumption through smart sensors	● Decisive Contribution	The developed method is aimed at utilizing the full potential of energy measurement and monitoring technologies
<u>GAP 4</u> Few guidelines are available on selection and use of energy-related KPIs	Support on design, definition and use of energy-related KPIs	● Modest Contribution	The cross-view method is detailed step-by-step that could help manufacturing companies develop and use firm-tailored e-KPIs
<u>GAP 5</u> Energy management decision support tools through KPIs are not well developed	Energy-related continuous improvement performance	● Modest Contribution	The e-KPI management phase demonstrates how the method and system of indicators are designed for the energy management in order to effectively use the information potential offered by the indicators
	Methods for understanding cause-effect relationships between production management and energy-related performance	● Decisive Contribution	The cause-effect relationships represent the core phase of the method, and develop a panel of variables that affect energy consumption. The related clustering is represented by the Ishikawa diagram, in which these variables are associated with different energy states of the machine tool through the cause-effect linkages

It leads to isolate a first scientific issue which is:

Definition and formalization of Energy Efficiency Indicator - EEI usable in decision-making process of industrial (manufacturing) system [Scientific issue n°1]

This first scientific issue is addressing only the EEI ... and not the other EE views. This consideration is not sufficient in the context of industrial decision-making. Indeed, EEI is

representative of an EE value but not on the evolution of this value. In that way, it is necessary to investigate the concept of EEP in which P is representative of EE performance allowing to discuss on “How and when energy is efficiently/inefficiently used?”.

2.2.3 EEP concept for evaluating the residual life energy

An answer to the following question cannot result only by focusing on EEI. Indeed, EEI is represented only by a value. This value needs to be compared with a **reference** to know if the system is energy efficient or not [51]. This reference should be representative of energy properties expected for the manufacturing system. It is named **EEI threshold**, technically and/or economically fixed in advance, given the current, past and future operation conditions, etc. In most of the cases, this threshold value is evaluated according to similar manufacturing facilities or best practices performance or from EE standard.

The comparison is normally done at a specific time. Thus it is a comparison at “discrete” time taking into account the past and current values of the EEI. It is not integrating the **potential evolution** of EEI [159]. Indeed, the consideration of the predicted EE evolution (taking into account the future values of impact factors) could be useful to determine the future time when the system is starting its operation in a non-energy efficient space. The difference between the future time and the current time can give advanced information about **EE performance** (not only to answer the question: is a component/system energy efficient or not? but also when will a component/system be considered as inefficient?)[160], [161].

Thus, this EEP value is assimilated to the **residual energy efficient time** to be used by the decision-makers to keep the control of the system in the energy-efficient space. Nevertheless, EEP is not really developed today in manufacturing system because it is difficult to assess the EEI evolution. It leads to isolate a second scientific issue which is:

Foundation of an energy efficiency performance (EEP) concept for evaluating residual life energy [Scientific issue n°2]

Indeed, the EEI evolution (due to component/system behavior) can be very different according to the setting/values of the different impact factors (e.g. operation mode, load profiles, new control technique, etc.). Thus it leads to EEP upheaval during all the system life by considering also the **system dynamics** (e.g. impact factors) [88], [89]. This upheaval is a real problem for EEP evaluation.

2.2.4 Evaluation of EEI/EEP in dynamic context

2.2.4.1 EEI as a function of impact factors

As explained before, EEI evolution can be very different according to the impact factors evolution (mainly, for example, degradation value, system age). It means that there are many difficulties to control global EE under the dynamics of the system. Thus, EEI (energy consumption and output) can be presented by a function which take into account these impact factors as its variables. Indeed, the evolution of impact factors can be random and/or stochastics e.g., EE of electrical power generated by photovoltaic system can be impacted by the environment temperature, dust development and sunlight radiation [67], [162]. It leads to consider also EEI evolution and EEP as **stochastic evolution**. In that way, one important step in the master of EEI/EEP is to select the right tool to predict the evolution of impact factors. This selection step can be referred to existing prognostic tools/approaches.

2.2.4.2 From existing prognostic approaches ... to a specific one dedicated for EEI prediction

Prognostics is fully defined by Voisin [163] as the prognostics process which aims to “*predict the future health of the system*”, and “*generate the different RUL (Remaining Useful Life) for each detected (current) or potential degradation/failure mode*”. Its goal is the prediction of how much time left before a failure on a system occurs, considering its current state, past and future operating conditions. Indeed, the prognostics concept has been introduced and successfully applied in various applications [164]–[167] mainly to predict the evolution of “health” conditions and then estimate the RUL. This prediction integrates the degradation evolution generally calculated from a set of data well representative of the past, and current health of the system. After that, this evolution and recorded failure events are used to estimate the RUL value. To support this prediction, various approaches have successfully been applied on different types of “health” conditions are experience-based prognostics, model-based prognostics and data-driven prognostics.

Nevertheless, the existing prognostics approaches are dedicated mostly to predict the evolution of one indicator of the system health (one by one without considering aggregated indicator) [163] which is not full satisfactory with the problem to support prediction of impact factors with regards to EEI/EEP. Indeed, regarding to the complexity of EEI/EEP (EEI is seen as a function of several impact factors), these existing prognostic approaches seem difficult even no longer to be directly applied for EEI prediction. It is needed to investigate new directions (ex.

combination of approaches) to support the expected prediction steps. It leads to isolate a third scientific issue which is:

Development of generic approach for prognostics of EEI at different levels of a manufacturing system [Scientific issue n°3]

Therefore, the EEI value and its evolution prediction (as analyzed in the previous sections) could be integrated in the decision making processes of the manufacturing system to master the EEI/EEP as close as possible on its nominal value. More precisely this mastering requirement can be supported by the maintenance decision-making process, mainly CBM one, by considering EE as a condition.

2.3 How to use EE in CBM strategies?

This consideration of EE in maintenance decision making-process and more precisely in CBM is directly related to challenge 2 defined in chapter 1. So, at this stage, it is important to focus on the assimilation of EE as a condition in CBM strategy (see section 2.3.1), and then on the assessment of EE-based CBM in terms of costs and benefits (see section 2.3.2).

2.3.1 Using EE as main condition for CBM strategies

From the maintenance strategies positioning developed in chapter 1, CBM has been identified as the best strategy among maintenance ones to achieve EE considerations because the maintenance action in CBM is decided at the right time on the basis of real monitored “conditions” of a manufacturing system (with regards to the right threshold). Indeed, CBM is performed when one or more indicators show that component/system is going to fail or that component/system performance is deteriorating (indicator value is over a threshold).

Thus, the tracking of this performance is generally done on conventional indicators (sometimes integrating energy considerations) but should be extended to sustainability requirements (in terms of degradation impact; EEI then EEP). Indeed, tracking a conventional indicator or a sustainable one could use the same techniques and brings similar advantages. In that way, the EEI/EEP (EEI or EEP) can be determined as the “condition” to be tracked to know if the energy performance of manufacturing system is deteriorating. In this case, if the EEI/EEP value is crossing the EEI/EEP threshold it is not leading to consider the component/system as failed but to consider the system as operating in a non-energy efficient space (it is crossing the border between energy efficient space and non-energy efficient space). Therefore, some

maintenance actions can be implemented for restoring EEI/EEP at the correct values (to go back to energy efficient space) knowing that these actions have to be justified also with regards to cost (direct and indirect ones for arguing on the benefits issued from restoring the EEI/EEP values) [7] [116].

Furthermore, EEI value at system level, which could be calculated from EEI value of individual components, presented the state of using energy efficiency for group of components, thus the possibility to develop the group of maintenance instead of based on individual maintenance.

Nevertheless, today EEI/EEP are not really taken into account in CBM and just a little in maintenance decisions in general. For instance, [16] proposed to use EE performance as an objective for maintenance by updating periodic maintenance on EE evolution, but mainly on mastering the deterioration of machine tool (a Markov process application). Moreover, [168] used the deterioration level of multi-bladed wind turbine system to raise the unplanned maintenance action for any failure items, while electrical energy as the useful output of this system is not fully taken into account.

So EE is mainly seen as an auxiliary result of these previous CBM planning. In addition, energy can be saved by optimal periodic preventive maintenance [7] or can impact preventive maintenance by considering energy consumption in the case of minimal repair [116].

In summary, EE in link with maintenance is mainly considered as an item to adapt preventive maintenance plan in terms of scheduled one but not in case of CBM strategy. So, an interest exist to focus on EE-based CBM while take into account the failure of machines/systems.

2.3.2 Evaluation of the EE-based CBM

This interest need to be demonstrated mainly by underlining the real added value (the benefits) of EE-based CBM. In conventional way, the evaluation of CBM added value is done with regards to cost. Indeed, cost is a main criteria in maintenance for finding the optimal maintenance strategy [169]. More precisely, the existing cost-models of CBM focuses mainly on the maintenance cost which is composed of preventive cost, inspection cost, corrective cost, etc. The energy cost may be not directly present in the sum of costs [170], [171]. It means that an evolution towards EE-based CBM should integrate also the impact on energy cost to the total cost in the way to find maintenance action optimization.

This energy cost can be related for a major part by implementing the “required monitoring” of the EEI/EEP. The monitoring can be done by sensors (direct monitoring) or by inspections knowing that implementing a monitoring system can reduce the cost and frequency of inspection task but increases the capital investment of the manufacturing system [95], [172]. For example, Jin [173] used power consumption to map all potential failure modes with railway point machines without deploying directly inspection task. So, an energy monitoring system can be used to locate faults in manufacturing system [23] which can help to reduce the inspection time and related costs (e.g. production loss when implementing inspection task).

In summary, this EE consideration in CBM in terms of “condition” but also in terms of the benefits to be supported (with a specific focus on cost by integrating inspection cost, sensor cost etc.) leads to isolate a fourth scientific issue which is:

Foundation of EE-based CBM [Scientific issue n°4]

2.4 Conclusions

The chapter 2 focused, from the two challenges identified in chapter 1, on the scientific problem statement related to them. It leads to defend EEI as an emergent sustainability indicator and as relevant KPI for maintenance decision-making in manufacturing system. EEI is then considered through its evolution in the dynamic context of the system to argue the EEP concept. These static and dynamic considerations of EE allows to conclude on the pertinence of EEI/EEP on several abstraction levels (component, function, system level) of manufacturing system in the way to aid decision-making. Finally, investigation of integrating EEI/EEP into CBM strategies is studied.

Therefore, from the problem statement developed, we have positioned 4 main scientific issues:

- *Definition and formalization of Energy Efficiency Indicator - EEI usable in decision-making process of industrial (manufacturing) system (Scientific issue n°1);*
- *Foundation of an energy efficiency performance (EEP) concept for evaluating residual life energy (Scientific issue n°2);*
- *Development of generic approach for prognostics of EEI at different levels of a manufacturing system (Scientific issue n°3);*
- *Foundation of EE-based CBM (Scientific issue n°4).*

These scientific issues are the basis to found our contributions developed then on the next chapters as follows:

Chapter 3 tackles the scientific issue n°1 and n°2, by detailing the EEI/EEP concept and develop a generic formalization of EEI/EEP at each level of abstraction (component, function, system) of an industrial system.

Chapter 4 addresses scientific issue n°3 by proposing a generic approach for prognostics of the evolution of EEI allowing to estimate the time left before the manufacturing system loses its energy efficiency property.

Chapter 5 aims at validating the contributions developed in chapter 3 and 4. In that way, the contributions are applied on TELMA platform.

Chapter 6 tackles scientific issue n°4 by contributing with the foundation of integrating EE into CBM decision-making. This contribution is also illustrated in TELMA platform.

Chapter 3

EEI and REEL: concept and formulation for industrial applications

3.1. Introduction

This chapter describes the contributions we proposed with regards to the two first scientific issues identified in chapter 2. In fact, we present an EEI concept with consideration of time-dependent degradation behavior for manufacturing systems at several abstraction levels such as component, function/system levels. In addition, the quantification of EEI by means of EEI formulations is proposed to evaluate its values. Since EEI may deteriorate with time, a question arising is when EEI reaches its critical threshold which could be seen as an energy efficiency property/target to be guaranteed. In that way, we propose a novel concept, namely the Remaining Energy-Efficient Lifetime (REEL), for representing energy efficiency performance (EEP) in an anticipation vision. REEL can be used for various decisions-making processes but mainly in maintenance ones (e.g. maintenance optimization) to be consistent with the frame of this thesis.

3.2. Concepts of energy efficiency indicators for industrial systems

As already defended in chapter 1, in manufacturing systems, both energy consumption and useful output [47], [57], [81] are two main information to be mastered by owner. The characteristics of this information allow to form the different categories of EEI normally usable at the different abstraction levels of the decision-makers mainly in terms of energy consumers and usage functions. Nevertheless, any of these categories can be used directly to fix these EEI requirements as shown in Table 4 of chapter 1 and leading to a first part of the scientific issue n°1 which is related to EEI identification. In that way, we propose a more general classification of these EEIs based on their potential applications (Figure 8).

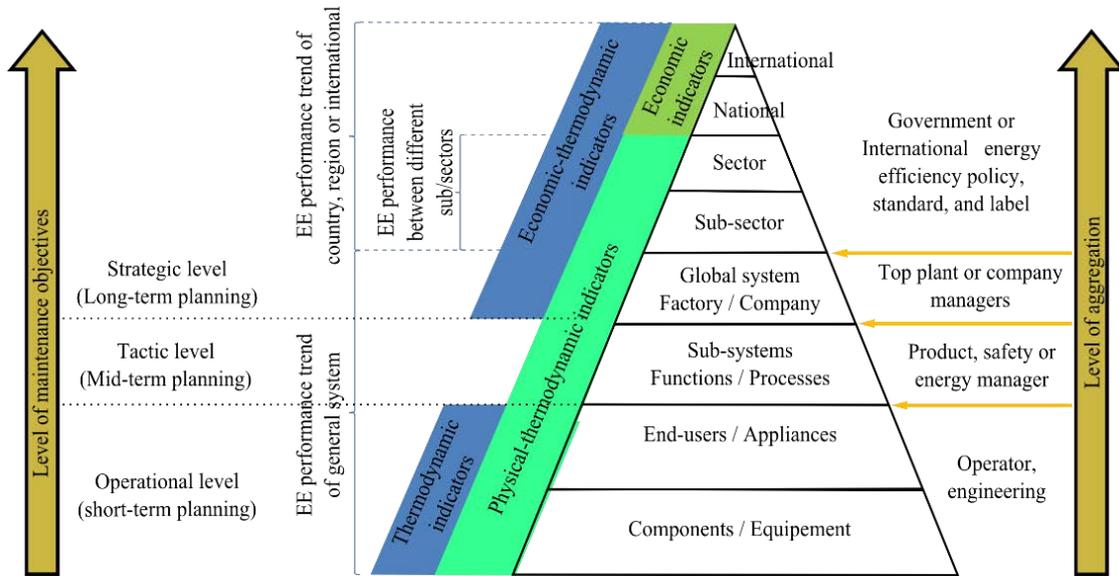


Figure 8. Concepts of EEI and their potential applications [174]

This classification highlights that the different EEI concerned by manufacturing levels are located from “global system” to “components/equipment” (level aggregation axis). Moreover, only the category related to “physical-thermodynamic indicators” (see chapter 2) is highlighted to serve as a basis for formulating these EEI on these levels. Indeed, physical-thermodynamic indicators integrate items as energy consumption and products delivery. Thus, based on the category of physical-thermodynamic indicators, and to answer to the formulation need express in scientific issue n°1, we propose, for manufacturing, to define EEI as:

$$EEI = \frac{E}{O}, \quad (3.1)$$

where E is the total used energy input, O is the useful output in physical units.

By definition, EEI provides the amount of energy consumed to produce a useful output unit. So, the lower the EEI value is, the lower consumed energy to produce one unit of useful output. EEI could be used in various decision-making processes, e.g., maintenance, control decision-making. For example, based on the current value of EEI of a component, efficiency of the component in using energy can be evaluated, and then decision-makers can choose whether to trigger a preventive maintenance action on components or not.

In link to the decision-making needs, the previous formulation has to be investigated on different abstract levels. In the frame of thesis, we focus only on two layers: component level and function/system one.

3.2.1 Energy efficiency indicator at component level

The “component” is seen as the basic element which works with others at downstream level to perform the function of upstream level. By using Equation (3.1), EEI of a component i at time t is defined as follows:

$$EEI^i(t) = \frac{E^i(t)}{O^i(t)}, \quad (3.2)$$

where $E^i(t)$, $O^i(t)$ are respectively the energy consumed and the useful output of component i within one time unit (from $(t-1)$ to t). The time unit could be an hour, a day, a month, etc. depending on the time interval of decision-making. We assume that the output of component i is unique and measurable. It should be noted that when the output of a component is uncountable or invisible such as when an electrical equipment or production process unit is pending and its auxiliary system may however remain running and consuming energy, the definition of EEI is slightly different. In fact, in this case, EEI is the ratio of energy inputs to energy outputs [175]. In that way, $O^i(t)$ in Equation (3.1) represents the energy useful output (hidden in physical outputs) and EEI mean (consist with the thermodynamic indicator).

In fact, component i may consume different kinds of energy sources which comes in different common forms (gas, fossilized fuels, electricity, light, etc.) and measured by International System (SI) of Units (Btu or BTU (British Thermal Unit), ton of coal equivalent (tce), kilowatt-hours (kWh), Joules (J), etc.). Thus, to calculate the total energy of a component, its energy inputs expressed in different forms need to be converted into a common unit. Then, the total energy consumption of component i , which uses different energy sources (measured by tons of coal, kWh, etc.), can be calculated with following formulation:

$$E^i(t) = \sum_{j=1}^1 \theta_{ij} ET_{ij}(t), \quad (3.3)$$

where $E^i(t)$ is the total energy consumed by component i , $ET_{ij}(t)$ is the amount of consumed energy sources j ($j=1-l$), θ_{ij} is energy conversion factor of the energy type j to the common energy unit of component i . The conversion factor θ_{ij} between different energy units is based on the SI units, e.g., $1 Wh = 3.412 Btu$, $1 tons of coal = 19,882,000 Btu$. The energy consumption $ET_{ij}(t)$ of energy type j (measured by Wh, Btu, etc.) can be monitored or calculated directly by different power meters.

In the same manner, component i may produce different types of products/services. A common product (the number/hours of services, tons of steel, etc.) needs to be defined to measure the amount of useful output. The output conversion factor of each type of product is the amount of common output which is considered equivalent to one unit. Actually, the output conversion factor for each product is fixed in advance by the decision-maker. In that way, if component i produces m types of product in one period, its total outputs measured/converted in common unit of output can be calculated as:

$$O^i(t) = \sum_{j=1}^m \gamma_{ij} OT_{ij}(t), \quad (3.4)$$

where γ_{ji} is the conversion factor of the output type j in the common unit of output of component i , and $OT_{ij}(t)$ is the amount of product type j ($j=1-m$).

Example 3.1:

Consider a system which is composed of 3 machines M1, M2 and M3. The structure of the system is shown in Figure 9. The physical output of the system, namely product B, is processed through two phases: phase 1 on machine M1 and phase 2 on machines M2 or M3. The intermediate products A, which is the physical output of machine M1, are needed to produce the final product B of system. 60% output of M1 enters M2 and the rest enters M3. It is assumed that, at time t , the energy consumption of M1, M2 and M3 is 20kWh, 3412 Btu and 30 kWh respectively. The useful outputs of M1, M2, and M3 are 200, 40 and 60 products per hour respectively.

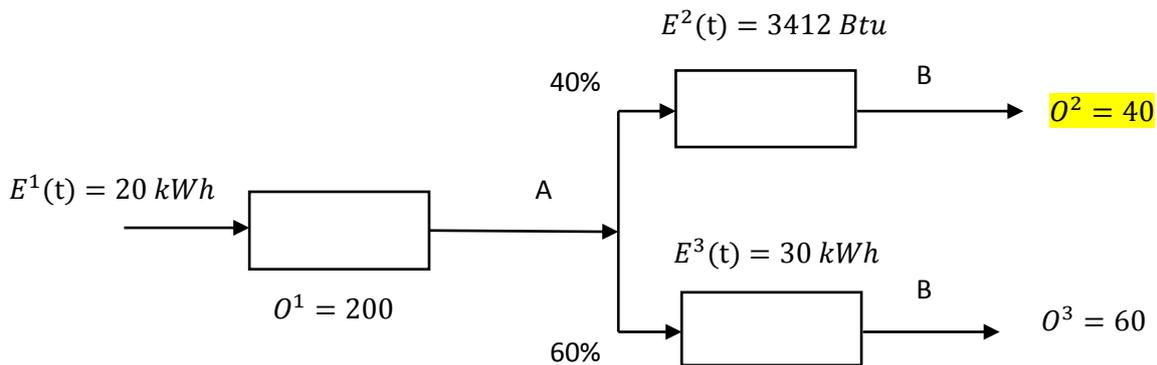


Figure 9. Manufacturing system of 3 components

By using Equation (3.2), we obtain EEIs at the component level. Hence, EEIs for M1, M2 and M3 are $EEI^1(t) = \frac{20}{200} = 0.1$ (kWh per product), $EEI^2(t) = \frac{3412}{40} = 85.3$ (Btu per product), and $EEI^3(t) = \frac{30}{60} = 0.5$ (kWh per product) respectively.

3.2.2 Energy efficiency indicator at the function/system level

We focus now on a function or system which is composed of n components interconnected according to a given configuration. It is assumed that only one kind of useful outputs of the function/system is considered. We are interested in the evaluation of EEI for this function/system from the EEI values at component level by bottom-up methods.

Based on Equation (3.2), EEI for this function/system is expressed as follows:

$$EEI^{\Sigma}(t) = \frac{E^{\Sigma}(t)}{O^{\Sigma}(t)}, \quad (3.5)$$

where $E^{\Sigma}(t)$, $O^{\Sigma}(t)$ are the total energy consumption and the total useful outputs during one time unit (from $(t-1)$ to t).

In one hand, we assume here a unique unit of E^i for each component i . The unique unit of energy input for different components may also be different. To evaluate the total consumed energy of the function/system, all energy input of downstream components need to be converted to a common one, e.g. kWh. Moreover, $E^{\Sigma}(t)$ may not equal the sum of the total input energy of each component [57] due to the energy transformation from upstream components to downstream ones according to the energy flows direction. Nevertheless, the total input energy of a function/system can be calculated from the input energy of its components. In that way, we propose the following evaluation equation:

$$E^{\Sigma}(t) = \sum_{i=1}^n \lambda^i E^i(t), \quad (3.6)$$

where λ^i represents the energy **weighting factor**. An energy weighting factor of any component link directly to its consumed energy and energy-losses (cannot be transferred to other components), which mainly depend on the dynamic context of the manufacturing system (formulated as impact factors in EEI formalization). As an illustration, for the manufacturing system above (Example 3.1), all components directly consume the imported energy and unique unit of the total consumed energy is kWh, thus $\lambda^1 = \lambda^3 = 1$ and $\lambda^2 = 0.000293$. As a result, the total consumed energy is $E^{\Sigma}(t) = E^1(t) + 0.000293 * E^2(t) + E^3(t) = 60$ (kWh).

On the other hand, the output may have different types of products/services. The converting task to add multiple forms of outputs should be considered. In this case, it is needed to consider the weighting factor of separate systems or unit processes to produce one output type as:

$$O^{\Sigma}(t) = \sum_{i=1}^n \mu^i O^i(t), \quad (3.7)$$

where μ^i stands for the output weighting factor associated to component i . In case of the common form of physical output volume is fixed at this upstream level, the output weighting factor μ^i can be used to express the change in the real physical output of each component at downstream level, and the variation in the prices effects has been ignored to avoid the impact of having different units [131], [176]. The weighting factors for different products present appropriately the amount of energy needed to produce each of the products [176] and remaining constant for all time points in the analysis.

Although Equation (3.5) can be used to calculate EEIs at upstream levels, but it can demonstrate the relationship between the EEIs of upstream levels and downstream levels of industrial system. By replacing the measured/stochastic values of total energy consumption and total physical output presented, with calculated values by Equations (3.6), (3.7) into Equation (3.5), EEI for a function/system is defined as:

$$EEI^{\Sigma}(t) = \frac{\sum_{i=1}^n \lambda^i E^i(t)}{O^{\Sigma}(t)} = \sum_{i=1}^n \lambda^i \frac{O^i(t) E^i(t)}{O^{\Sigma}(t) O^i(t)} \quad (3.8)$$

$$\rightarrow EEI^{\Sigma}(t) = \sum_{i=1}^n \lambda^i \omega^i(t) EEI^i(t) \quad (3.9)$$

$$\text{with } \omega^i(t) = \frac{O^i(t)}{O^{\Sigma}(t)} \quad (3.10)$$

It is clear that Equation (3.9) allows evaluating EEI of a function/system from EEIs of its components. These weighting factors may be not always available and need to be estimated. Furthermore, they are may be time-dependent. It should be noticed that several approaches have been proposed to support the weighting factors consideration for energy efficiency applications (energy consumption and output) at multi-levels of industrial sectors [27], [131]. For example, several approaches can be used to calculate these weighting factors [27], [53], [176]–[178].

Example 3.2:

Reconsider the example 3.1 presented in Figure 9, the total output of the system is $O^{\Sigma} = O^2 + O^3 = 100$ products per hour ($\mu^1 = 0, \mu^2 = \mu^3 = 1$). EEI for the system can be calculated in

two ways. By using directly its definition presented by Equation (3.5), we get $EEI^\Sigma = \frac{E^\Sigma}{O^\Sigma} = 0.6$ kWh per product. We can also obtain EEI^Σ using the aggregation model presented by Equation (3.9): $EEI^\Sigma(t) = \sum_{i=1}^n \lambda^i \omega^i(t) EEI^i(t) = 1 * 2 * EEI^1 + 0.000293 * 0.4 * EEI^2 + 1 * 0.6 * EEI^3 = 0.6 \left(\frac{\text{kWh}}{\text{product}} \right)$ with $\omega^1 = \frac{O^1}{O^2+O^3} = \frac{200}{100} = 2$; $\omega^2 = \frac{O^2}{O^2+O^3} = \frac{40}{100} = 0.4$; $\omega^3 = \frac{O^3}{O^2+O^3} = \frac{60}{100} = 0.6$ and $\lambda^1 = 1$; $\lambda^2 = 0.000293$; $\lambda^3 = 1$.

So these two Equation (3.5) and (3.9) are presented to calculate the EEI at upstream levels to tackle the scientific issue n°1 about the formalization of EEI at system level (with EE data of components). Indeed to calculate the EEI in the link from the downstream levels to the upstream levels, the mathematic Equation (3.5) can be used to directly calculate the EEI at upstream level when the measure of energy and physical output is available. By the same principle to convert the different forms of energy and physical units, the weighting factors of each component at downstream levels need to be calculated to estimate the final EEI at upstream level (Equation (3.9)). EEI may be subjected to degradation with time due to the evolution of the manufacturing system and its environment.

3.3.Remaining Energy-Efficient Lifetime

As presented in the chapter 2, mastering the EEI during the lifetime of industrial system (knowing its evolution) can provide useful information for decision-maker during the decision-making process. It means to consider EEI not only as a value but also its evolution as advocated by EEP concept.

3.3.1 Concept of the Remaining Energy-Efficient Lifetime

It has been shown in a large number of works such as [52], [63], [158] that the energy consumption and/or the useful output of an object (component, function or system) are usually subject to degradation with time due to aging phenomena and/or the evolution of the operating conditions. As a consequence, EEI may deteriorate with time. In relation to this degradation, we can define a critical threshold, denoted $EEI_{Threshold}$, by which an manufacturing object (component, function/system) is considered as having lost its energy efficiency property when its EEI value reaches the critical threshold. In that way, from a practical point of view, it is interesting to know when the object loses its energy efficiency property as highlighted in chapter 2 (see section 2.2.3). This specific period of time (between current time and expected time when the manufacturing system starts using energy inefficiently) leads to estimate the residual energy

efficient life of manufacturing (EEP). To this end, we propose a concept, namely the REEL, present the remaining energy-efficient lifetime. This REEL is equivalent to the EEP and leads to give answer with regards to scientific issue n°2 (chapter 2).

Indeed, REEL of an object is defined by the time left before an object loses its energy efficiency property which is technically and/or economically fixed in advance, given the current condition, past and future operation profiles. Mathematically, REEL at time t can be expressed as:

$$REEL(t) = \{(T: EEI(t + T) = EEI_{Threshold} | EEI^t < EEI_{Threshold})\} \quad (3.11)$$

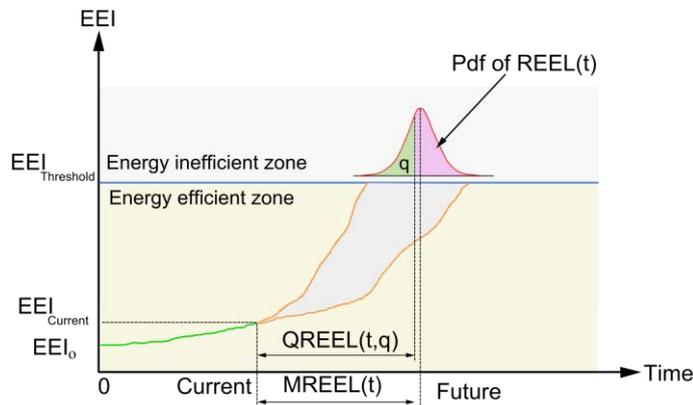


Figure 10. Illustration of the REEL and its variants

By definition, if $EEI(t)$ evolves stochastically, $REEL(t)$ is then a positive random variable. In this case, several variants of the REEL can be specified:

- Mean Remaining Energy-Efficient Lifetime (MREEL) is defined as the mean time left before an object loses its energy efficiency property. Mathematically, $MREEL$ at time t can be defined as:

$$MREEL(t) = E[REEL(t)], \quad (3.12)$$

where $E[x]$ is the mathematical expectation of x .

- Remaining Energy-Efficient Lifetime with a given probability q , namely QREEL, is defined as the left time before an object loses its energy efficiency property with a given confident level q :

$$QREEL(t, q) = \sup\{v: P(EEI(t + v) < EEI_{threshold}) = q | EEI(t) < EEI_{threshold}\} \quad (3.13)$$

It is clear that MREEL and QREEL are deterministic. As a consequence, their uses for decision-making could be simpler than REEL. Figure 10 illustrates the concept of the REEL and its variants.

3.3.2 Evaluation of the Remaining Energy-Efficient Lifetime at component level

By definition, to evaluate the REEL of a component, it is necessary to quantify the potential evolution of EEI. The energy consumption and/or the useful output may depend on different impact factors. As a consequence, it is important to identify several impact factors/features that impact the energy consumption and/or the useful output of a component. In a general manner, we classify these impact factors into two categories: static factors (SF) which are impact factors whose evolution in time is deterministic and often known in advance (e.g., production planning/load profiles, human skills, etc.); dynamic factors (DF) whose evolution in time is random and often unknown, e.g., environment condition, deterioration features, etc. To predict the evolution of the DF, several existing prognostic approaches (see chapter 4.2) may be used.

Based on the value of these impact factors, the energy consumption $E^i(t)$ and the useful output $O^i(t)$ may be directly evaluated. However, if the relationships between the impact factors and the energy consumption/useful output may be stochastic and unknown, an estimation is then needed.

In that way, a generic model of energy efficiency based on the proposed formulation of energy consumption $E^i(t)$ and useful output $O^i(t)$ are the following:

$$EEI^i(t) = \frac{f(t, SF^E, DF^E)}{g(t, SF^O, DF^O)} \quad (3.14)$$

$$E^i(t) = f(t, SF^E, DF^E) \quad (3.15)$$

$$O^i(t) = g(t, DF^O, DF^O) \quad (3.16)$$

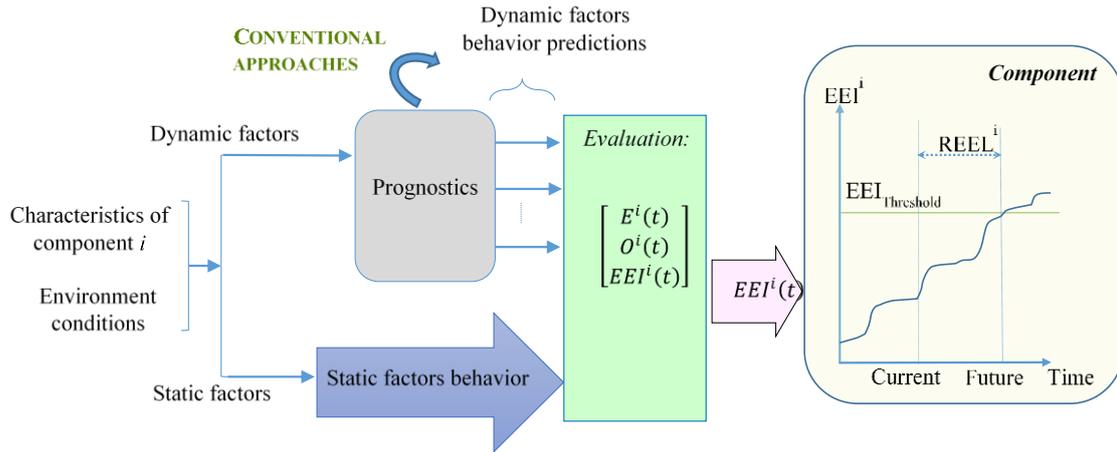


Figure 11. The REEL evaluation at the component level

It is important to note that f and g may be nonlinear or stochastic. Based on the future evolution of EEI, the REEL can be evaluated. The illustration of the REEL evaluation process is given by Figure 11.

Example 3.3:

We are considering another example related to water supply systems, for the consideration of its EEI as a function of different impact factors. In relation to this system, [140] proposed the equation to calculate the energy consumption:

$$C_{EL} = \frac{\rho \cdot g \cdot Q \cdot H}{\eta_B \cdot \eta_M} \cdot \Delta t = \frac{\rho \cdot g \cdot Q \cdot (H_G + \sum \frac{f \cdot L \cdot v^2}{D \cdot 2 \cdot g} + \sum \frac{k \cdot v^2}{2 \cdot g})}{\eta_B \cdot \eta_M} \cdot \Delta t \quad (3.17)$$

Where:

C_{EL} is the energy consumption by each motor-pump set [Wh];

ρ is the water density [kg/m³];

g is gravity acceleration [m/s²];

Q is the pumped flow [m³/s];

H is the total height of the pump lift [m];

η_B and η_M are pump and motor performance respectively [%];

Δt is the running time of the motor-pump set [hours];

H_G is the geometric head of the elevation [m];

f is the pipe friction factor [0-1];

L is the pipeline length [m];

v is the average flow velocity in the pipe [m/s];

D is pipe diameter [m];

k is the coefficient of head loss of each singularity [0-1].

If the useful output is considered as the total volume of delivered water, the total output can be calculated as:

$$O_{EL} = Q \cdot \Delta t \text{ (m}^3\text{)} \quad (3.18)$$

$$EEI_{EL} = \frac{\rho \cdot g \cdot (H_G + \Sigma \frac{f \cdot L \cdot v^2}{D \cdot 2 \cdot g} + \Sigma \frac{k \cdot v^2}{2 \cdot g})}{\eta_B \cdot \eta_M} \text{ (Wh/m}^3\text{)} \quad (3.19)$$

In link to our frame, the two impact factors (geometric head (H_G) and length of pipelines (L)) are considered as static factors. Their values can be changed during the time but are known in advance based on load development plan. The other impact factors (pump (η_B) and motor (η_M) efficiencies, pipe friction factor (f), quantity and condition of singularities (Σk)) are considered as dynamic factors. By using the Equation (3.19) with the predicted value of its impact factors, the EEI value of pumping can be predicted.

It is important to note that predicting the evolution of EEIs is a difficult task and cannot be based on only one prognostics approach. For example, the deterioration of bearing, which impacts the energy efficiency performance of rotating machines, may be predicted based on vibration signals by using data-driven prognostic approaches [107], [179].

3.3.3 Evaluation of the Remaining Energy-Efficient Lifetime at higher level

At the function/system level, the operation programs or system functions have strong impacts on the running modes of each component. An efficient equipment could lose its optimal working point with regard to the running modes of the system. In this case, there is a high opportunity in energy efficiency improvement at system level due to the non-optimal working points, lack of skills of operators or low awareness of managers [60].

Firstly, the energy consumption and the useful output of lower level units can be changed according to various system structures, which are defined as set of operation procedure of lower level units i.e. components. Indeed, several operation profiles can be implemented to conduct

functions of an industrial system. Thus the contribution of each lower level unit to the energy consumption and the useful output of higher levels may be modified thereby. For example, in the hot-dip galvanized steel sheet production process, if the thickness of steel sheet output is decreased, the motor-driven roller system will consume more electrical energy while the energy consumption of the auxiliary systems like lighting and conveyors is seen unchanged. The system boundaries, constraints and future operation profiles that can impact EEI have to be identified and classified [180].

Instead of only using the predicted energy consumption and the useful output of lower level components, the contribution of all components is requested to calculate EEIs at the function/system level. The contributions of components are influenced by future operation plans which can be a set of operation modes corresponding to any forecasted production requirements. From Equation (3.9), $EEI^\Sigma(t)$ for a function/system at any time point t is affected by the weighting energy factors, the weighting physical factors of all components and other parameters such as system structures, dependencies between components, production schedules, support systems, operation conditions and management. Information on the function or system will be used to assess the weighting factors associated with overall energy consumption and those related to productivity. It is necessary to note that these factors may change over time. Figure 12 illustrates the process of predicting REEL at the level of a function or a system.

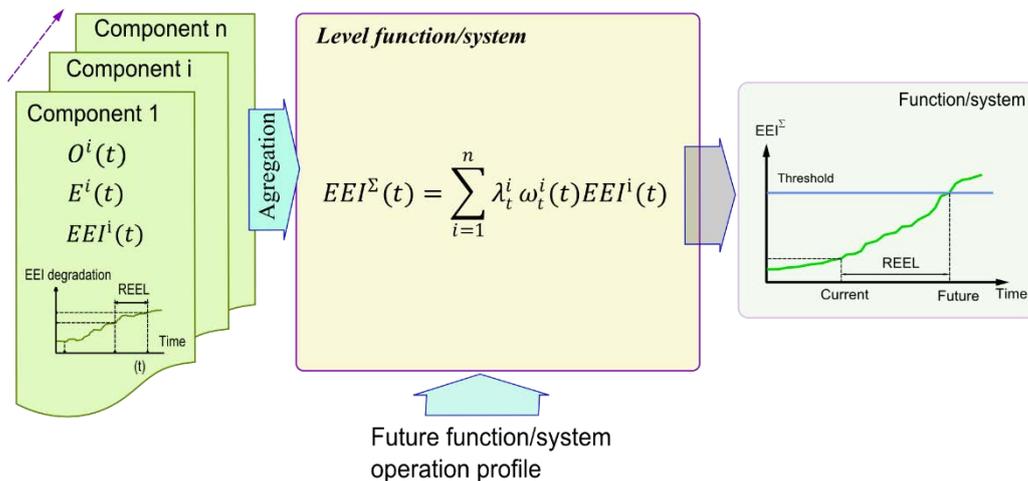


Figure 12. Procedure to evaluate REEL at function/system level

At this stage now, it is necessary to predict the potential evolution of EEIs in order to estimate the REEL. It is however noticed EEIs may depend on different factors (SF and DF), hence predicting the potential evolution of EEIs may be not easy.

3.4. Conclusion

In this chapter, with regards to the first scientific issue, an energy efficiency indicator (EEI) based on the physical-thermodynamic indicators analysis is defined at both component and function/system level of a manufacturing system. This EEI concept is developed to be consistent with existing EE standards/frameworks. It can be expressed as the ratio of energy input over the useful output of industrial system and this for different abstraction levels. Then a general formulation of EEI is proposed by taking into account the static and dynamic impact factors by using Equations (3.14), (3.15), and (3.16). In order to evaluate the EE performance to tackle the second scientific issue, a novel concept namely remaining energy-efficient lifetime (REEL) providing the time left before a component/function/system losses its energy efficiency property is proposed. This concept can be seen as a transformation of RUL concept and the generic formalization of REEL is constructed on the Equations (3.11), (3.12) and (3.13). In that way, REEL is representative of EEP in the future. Based on the developed concept and formulation of EEI/REEL, in the next chapter a generic approach will be developed to predict the potential evolution of EEI and estimate REEL.

Furthermore, the use of EEI/REEL in condition-based maintenance decision-making will be described in Chapter 6.

Chapter 4

Generic approach for prognostics of the evolution of EEI and REEL

4.1. Introduction

This chapter describes our contribution related to the scientific issue n°3 pointed out in chapter 2. As mentioned in chapters 1 and 2, predicting the evolution of EEI is crucial for estimating REEL. It is however shown that the existing prognostic approaches cannot be directly used to support this prediction due to the complexity of EEI. Therefore we propose, in this chapter, a generic approach which can help to select the appropriate existing prognostic approaches and their combination for predicting the potential evolution of EEI and estimating REEL. In that way, a short review on the existing prognostic approaches are firstly discussed. This provides a classification on the prognostic models and their potential applications. A generic approach for prognostics of EEI/REEL, from these existing prognostics models, at both component and function/function level is then proposed. This approach is based on the three steps and each step is detailed.

4.2. Short review on existing prognostic approaches for RUL prediction

Indeed, predicting the EEI evolution in link to the dynamic context of the system (e.g. impact factors) could be referred to the use of conventional prognostic approaches to predict the RUL of component/system. For the prediction of the RUL, a large number of prognostic approaches have been proposed and classified into three categories (Figure 13):

- **Experience-Based Prognostics:** This type of approach is based on the exploitation of knowledge on the failure or degradation of systems for the prediction of the RUL. Experience-based prognostic approaches are quite simple and less expensive to be implemented [181], [182]. However, these approaches are hardly applicable in a dynamic environment where a system and/or its environment evolve dynamically over time. Indeed, experience-based prognostic approaches strongly depend on the competence of experts and engineering. In addition, prognostic results are less accurate than model-based and data-driven prognostic methods. Nevertheless, this kind of approaches could be useful when historical data is very limited.

- Model-Based Prognostics:** These approaches are mainly based on analytical/mathematical models to describe behaviors of systems and mechanisms of degradation phenomenon [183], [184]. Main advantages of model-based approaches are their high accuracy and flexibility in configuring input data. Of course, prediction accuracy of these approaches depends on the precision of the presented models. Furthermore, nonlinear and stochastic characteristics of industrial systems may increase the difficulty in building analytical models. The flexible configuration of systems impact the model parameters. Thus, these situations have to be taken into account in the real-time modifications of these models.
- Data-driven Prognostics:** These approaches allow to identify trends/patents of a developing fault and to predict the amount of time before it reaches a predetermined threshold [185]–[187] using information from historical treated data (trained data). These prognostic approaches can identify the real-time health condition of a system by various techniques such as regression analyses, Bayesian algorithms, neural networks, fuzzy logics, support vector machine... These prognostic approaches are more precise than the first type of approaches (experience-based prognostics), in their ability to link with recognized system behaviors by experience methods. Despite no specific physical model is needed, the data-driven approaches require a monitoring system and learning time.

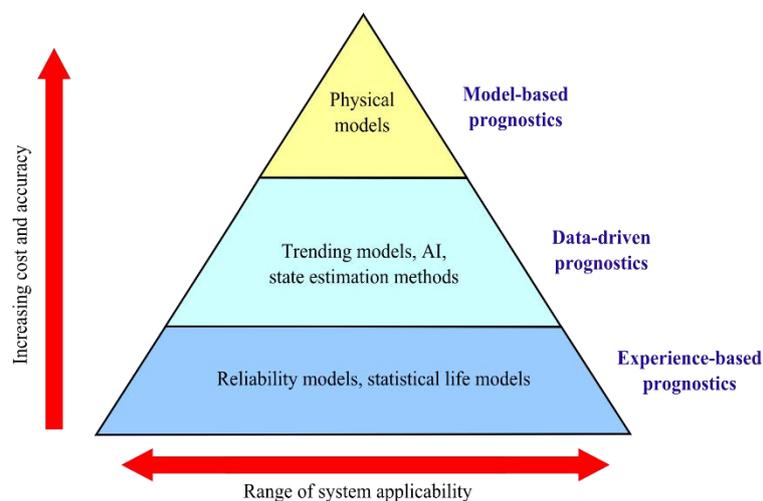


Figure 13. Classification of prognostic approaches [188]

Depending on the type of prognostics approaches, various types of information are required such as engineering models and data, failure history, past operating conditions, current

conditions, identified fault patterns, maintenance history and system degradation. Otherwise, RUL is mostly considered just for only one or scale “condition”, which is usually presented by only one degradation indicator.

As recently mentioned in several studies, the hybrid-prognostics are mentioned to leverage the advantages of different prognostics models [165], [189]. The basic principal of this work are combines two or three previous approaches in a close loop to get benefits and limit their drawbacks. More reliable and accurate prognostics results obtained by hybrid approach are claimed [190].

4.3. Global view of the proposed generic approach for prognostics of the EEI evolution and REEL

So, in link to the conventional prognostics approaches previously presented, we propose a generic approach for predicting the evolution of EEIs, which is structured on three main steps (Figure 14):



Figure 14. Generic approach for prognostic of the evolution of EEI

Step 1 – *Energy efficiency modeling*: The objective of this step is to formulate the energy consumption and the useful output. In this sense, first, several impact factors (degradation physical health, material quality, etc.) have to be identified and, then, the relationship between the impact factors and both the energy consumption and the useful output should be formulated. These impact factors already have been taken into account to develop the Equations (3.14), (3.15), and (3.16) of chapter 3.

Step 2 - *Prediction of the potential evolution of impact factors*: The objective of this step is to forecast the evolution of impact factors identified in Step 1 according to the future operation profiles. By using an appropriate prognostic model, the future evolution of these impact factors may be tracked.

Step 3 – *Evaluating the evolution of EEIs and estimating the REEL*: The aim of this step is to predict the evolution of EEIs, thereby estimating the REEL defined in Equation (3.11) by taking into account the results given in Step 2.

The procedure for applying a generic approach for prognostics of the evolution of EEIs is illustrated in Figure 15. This procedure can be developed both at the component level and at function/system levels. It is important to note that the process for components (the left part of Figure 15) is linked to the procedure for the function/system level (the right part of Figure 15). The following detailed procedures concretize and detail the generic approach leading to the scientific issue n°3 which is related to EEI prediction at different levels of manufacturing system.

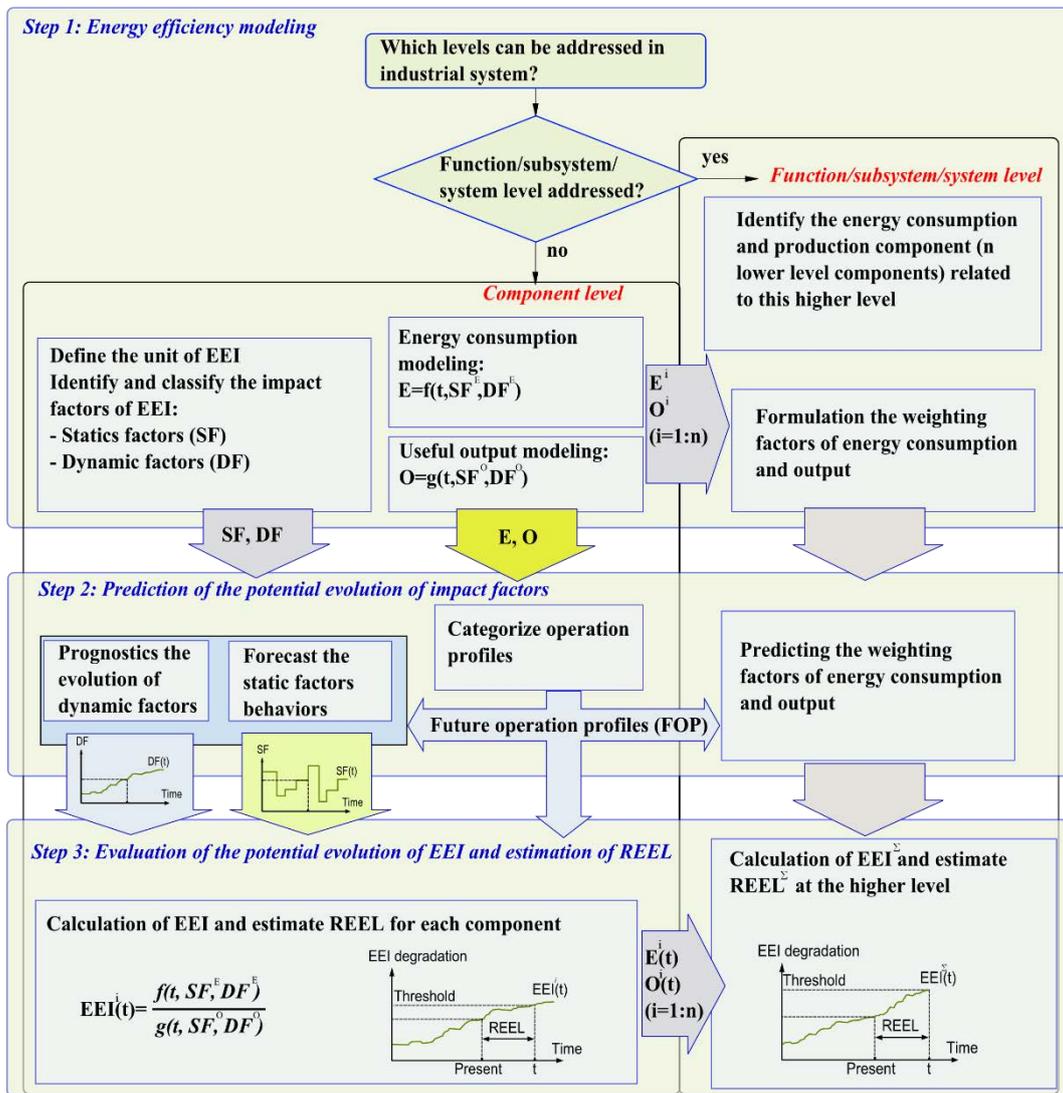


Figure 15. Generic approach for prognostic of the EEI evolution to estimate the REEL

4.4. Step 1: Energy efficiency modeling

As discussed in chapter 3 (section 3.2), it is necessary for modeling the energy efficiency (the energy consumption and the useful output) to calculate EEIs at different time points. The formulation of taking into account identified impact factors is the main achievements of this step.

Firstly, the abstraction levels of industrial systems, at which the prognostics approach has to be implemented for predicting the EEI evolution, should be addressed. Within industrial vision, the system is usually seen as multi-levels including component and function/system levels. Therefore, the bottom-up method should be applied to evaluate EEIs from the lowest downstream level (the component level) to the higher upstream levels (function/system level). The structure of levels can vary depending on the objective of decision-makers and how depth they can technically understand their system. So, it is required to identify the level on which the EE assessment has to be carried out.

As formalized in Equations (3.2) and (3.5), a clear definition of EEIs is an essential requirement to secure the measurable characteristics of EEIs. It means that the unit of both the energy consumption and the useful output need to be defined.

4.4.1. EEI at component level

To find out models of energy consumption and the useful output at the component level, we propose a procedure composed of two phases (Figure 16).

- Phase 1: Specifying parameters of the energy efficiency model. The objectives of this phase are to define the unit of EEI (the unique unit of the energy consumption and the useful output) and, then, to identify and classify the impact factors of EEI. This phase is based on three elements to specify the energy consumption and the useful output.

- The unit of EEIs at the addressed level should be defined. The list of common units, which are issued from recommendation of manufacturer, standards, codes, energy experts, or from similarity components/processes, should be referred to select the most suitable unit of EEIs for downstream components. For example the EEI unit for air-compressor can be kWh/m³ [138]. This common unit of each component will be kept unchanged for all life-cycle of manufacturing system to provide the comparable unit to quantify its EEI.
- The used units of the energy consumption and the useful output have to correspond to the defined unit of EEI. If there are different types of energy resources and product/services, they have to be converted to a unique unit as proposed in Equations (3.3) and (3.4). For example, by using again Figure 9, the unit of EEI for component 2 can be Btu/product and kWh/product at function level.

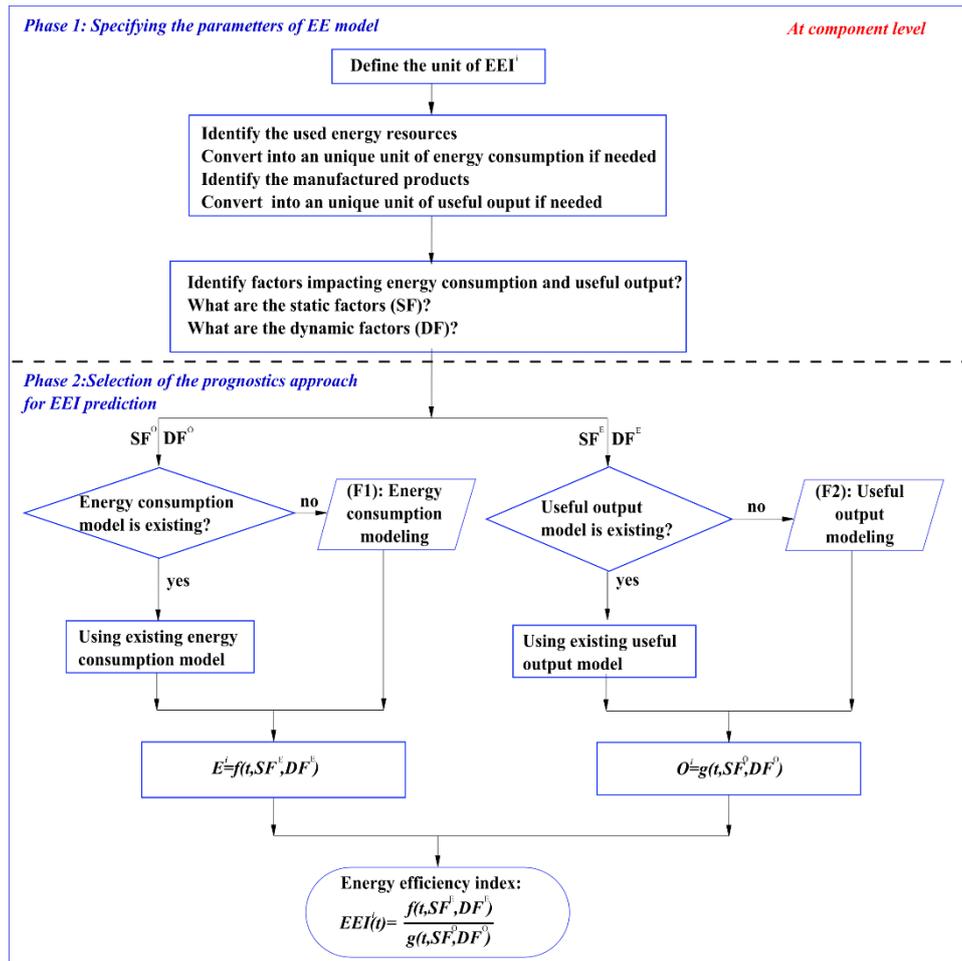


Figure 16. Diagram for modeling energy efficiency of manufacturing systems

- All impact factors of the energy consumption and the useful output should be identified and classified into SF and DF. This classification aims at defining what impact factors should be applied to prognostic approaches for predicting their evolution in the next step.

All available energy data is collected through the acquisition/monitoring system to provide efficient relevant data at different layers of the application.

- Phase 2: Selection of the prognostics approach for EEI prediction. If an energy efficiency model (energy consumption model and/or useful output model), which is a function of identified impact factors, already exists, this model can be used as the final selected energy efficiency model of the first step. Otherwise, models of the energy consumption and the useful output need to be developed. The proposed procedure to select and/or to develop an appropriate model for energy efficiency (process F1 for energy consumption modeling and

process F2 for the useful output modeling) is illustrated in detail in Figure 17. The latter leads to the following cases:

- If physical laws related to the energy consumption and the useful output are well understood and available, the model-based prognostics approach may be applied to build energy consumption and the useful output models;
- If historical data related to the energy consumption and the useful output with respect to identified impact factors are sufficient enough or recordable, the data-driven prognostics approach may be applied to build energy consumption and the useful output models;
- If experienced judgment and engineering are available or sufficient enough to formulate the energy consumption and the useful output, the experience-based prognostics approach may be used.

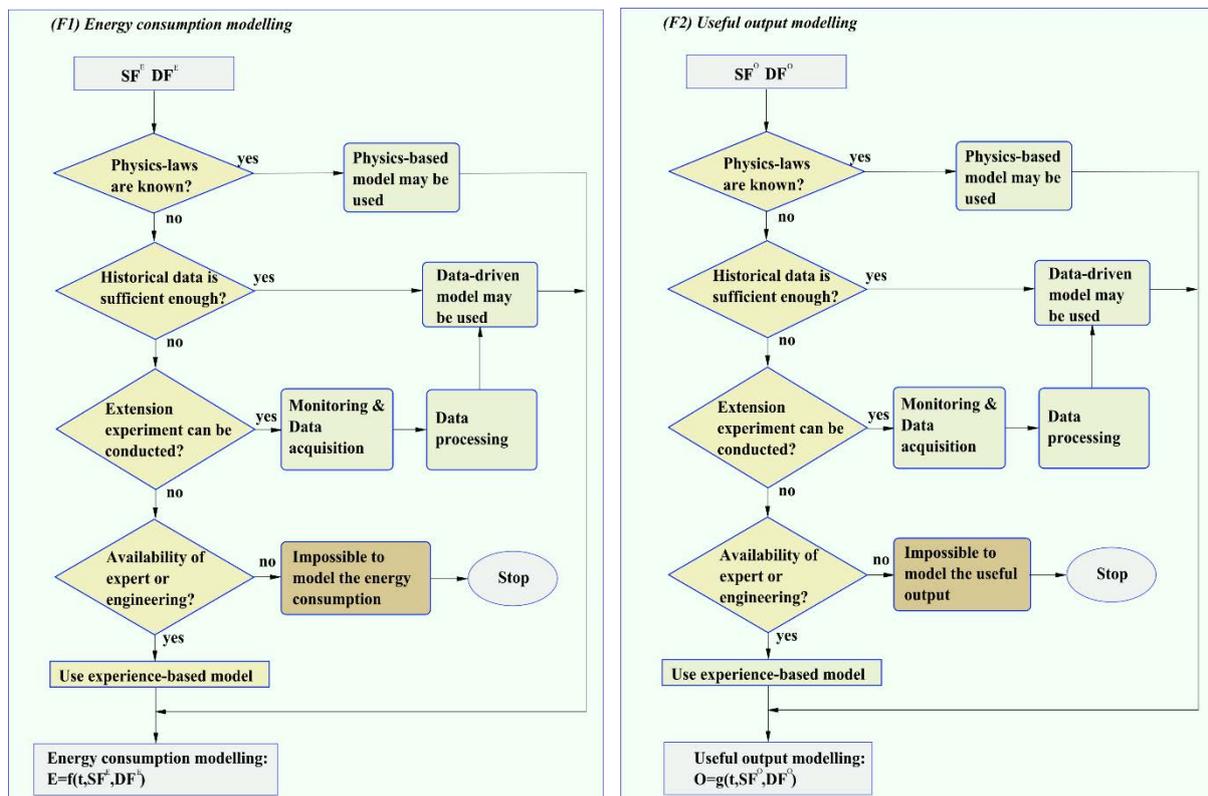


Figure 17. Procedure for prognostics approach selection of energy consumption and useful output modelling

Of course, if several prognostic approaches are applicable for the energy consumption and the useful output, the appropriate prognostics approach should be selected based on its accuracy.

In that way, the model-based prognostics should be the first priority in modeling (see section 4.2).

4.4.2. EEI at higher level

If a higher level has to be addressed, the definition of both input and output (energy and physical output) are firstly prerequisite to determine common units of each component at downstream levels and higher upstream level. Then, the main components contributing to the energy consumption and the useful output at this level should be identified (knowing that the energy efficiency modeling has previously been developed for each component). However, the contribution of the components is influenced by future operation plans of functions/systems. Thus the impact of function/system factors such as energy and work flows, management plans, production plans need to be taken into account.

In order to technically understand the transformation of both energy and material between components to produce the final manufactured product at higher level, an energy flows diagram and production diagram need to be provided in advance (by external energy experts or experience data). This allows to assess the hidden energy and resources in each unit of output, then to identify which components at downstream level can have strong contribution on the EEI at higher level (as well the areas that can have major change in the future). Indeed, the energy flow diagram is a graph which illustrates the energy transfer between components and how energy can be transformed and distributed between these components. Figure 18 illustrates the energy flow in the case of a fan system which is combined from three main components (the control system, the electrical motor and the centrifugal fan) [174], [191]. The figure shows the relationships and the effects of an individual component on the others.

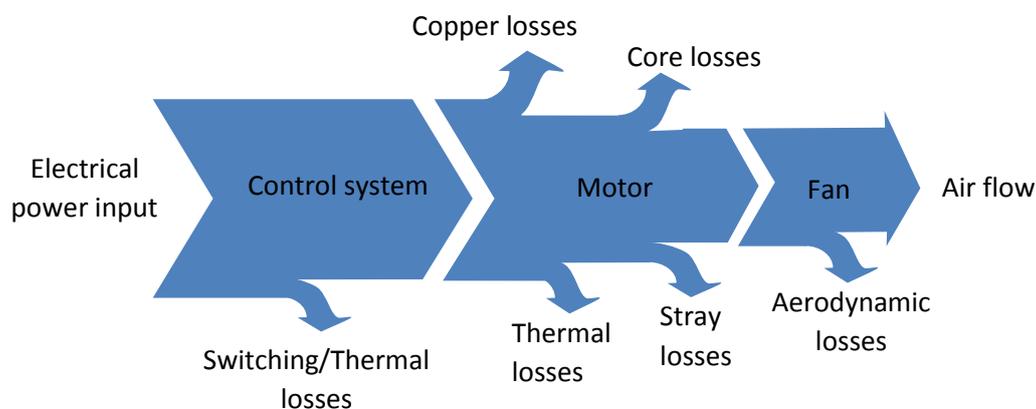


Figure 18. Energy flow and Air flow output of fan system

In that ways, energy and material flows are analyzed to realize the contribution of each component to the energy consumption and the useful output at this level. This is important to visualize how the input energy is distributed to downstream component. Then the impact of these components will be materialized by their weighting factors (λ^i, ω^i) as formulated in Equations (3.6) and (3.7). Then, the aggregate formulation for calculating EEIs as proposed in Equation (3.9) is used to estimate the energy efficiency performance at the function/system level. It is important to note that going from energy and material flow diagrams to weighting factors (λ^i, ω^i) might be not so obvious.

At the end of Step 1, the energy efficiency model (with the formulation of the energy consumption and the useful output) including the operation conditions (the impact factors and operation profiles) need to be achieved. The evolution in the future of the identified and classified impact factors will be predicted in Step 2. Then their evolution will be used with the energy efficiency model for predicting the evolution of energy efficiency at Step 3.

4.5. Step 2: Prediction of the potential evolution of impact factors

The second step of the proposed generic approach is to forecast the evolution of impact factors of the energy consumption and the useful output. This step is based on conventional prognostic approaches. In order to do so, the future operation profile (FOP) must be identified.

4.5.1. At component level

The potential evolution of the impact factors (both SF and DF), which are already identified and classified in Step 1, should be forecasted regarding to FOP. To support this task, a procedure is proposed and illustrated in Figure 19.

Firstly, SF, whose evolution in time is deterministic, are usually easy to be observed in advance. We just make a calculation of these SF at any time point in the future to forecast their evolution.

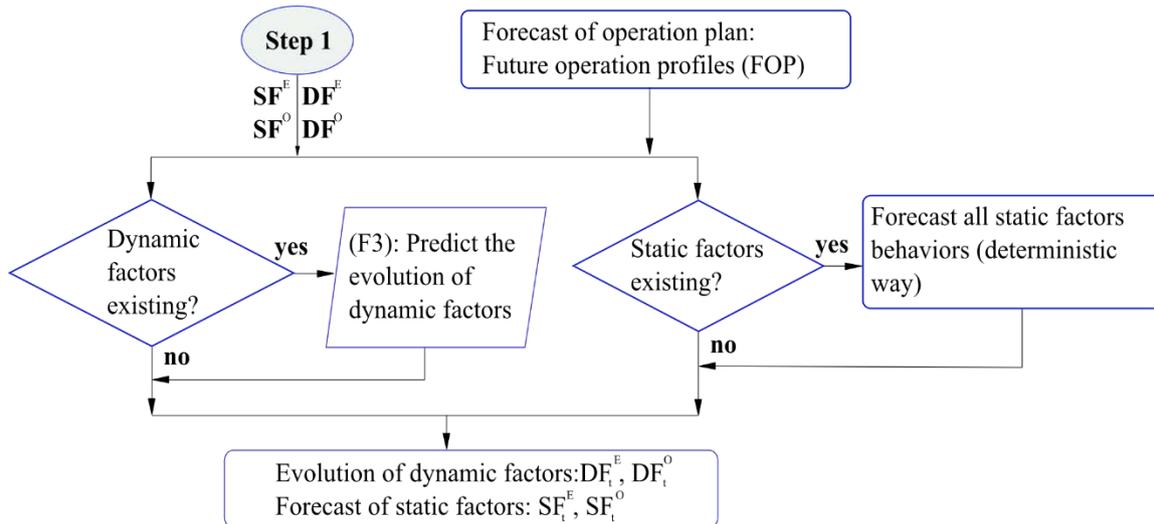


Figure 19. Procedure for predicting the evolution of impact factors of the energy efficiency model

Secondly, the future values of DF should be estimated by using conventional prognostic approaches. To this end, a procedure to select an appropriate prognostics approach for a dynamic factor is shown in Figure 20. The selection is based on the following cases:

- If the behavior and physical laws of a dynamic factor are well understood and available, the model-based prognostic approaches may be applied to predict the evolution of the dynamic factor;
- If historical data are sufficient enough or experiments can be implemented to record useful data, the model for the evolution of the dynamic factor may be built by processing and training the data. Then, the data-driven prognostic approaches should be applied to predict the trend of the evolution of the dynamic factor;
- If the experience-based model can be built based on the knowledge of experts and engineering, the evolution of the dynamic factor may be predicted by using experience-based prognostic approaches;
- If no prognostic approach for tracking the DF is founded, then the evolution of DF cannot be estimated.

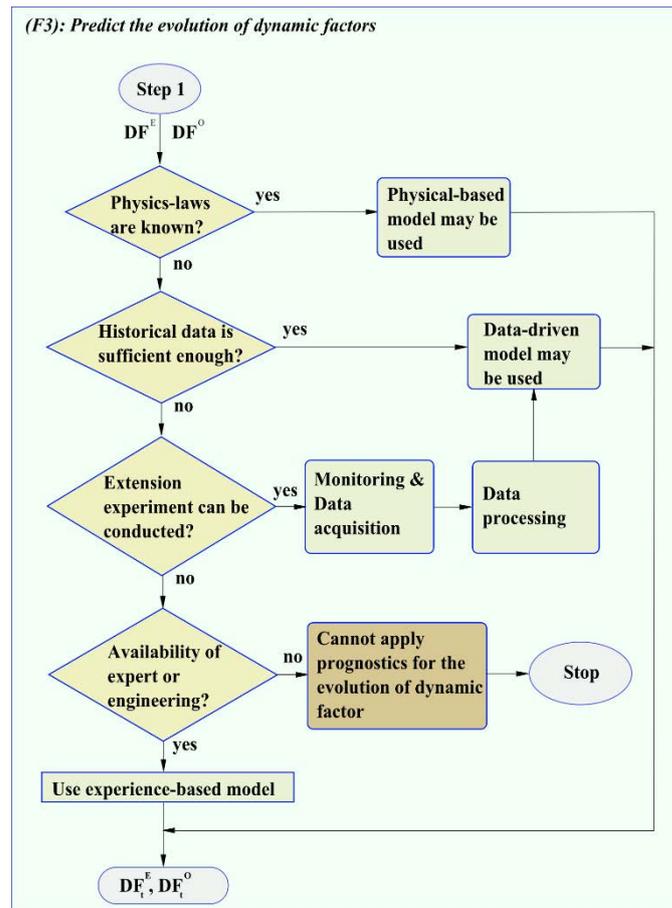


Figure 20. Procedure for selecting prognostic approaches to predict the evolution of a dynamic factor

4.5.2. At higher level

At this addressed level, the FOP may condition the configuration and operation mode of the components. In that way, the set of impact factors of all components has to be determined according to the modification of mission profiles in the future.

At first, the FOP should be analyzed to identify its impact on the energy and material flows within the addressed level. Then the contribution to the energy consumption and the useful output of each component will be converted into its weighting factor corresponding to different energy and material flows. At the end, a set of weighting factors of all components are collected at any time point in the future.

It is essential at the end of Step 2 that the evolution of both dynamic and static factors needs to be forecasted. Their evolution will be used by the energy efficiency model to evaluate the evolution of energy efficiency in the next step under future mission profiles.

4.6. Step 3: Evaluation of the evolution of EEI and estimation of REEL

The objectives of this step are to evaluate the potential evolution of EEIs and to estimate the REEL regarding to a future condition. This step can be divided into two phases (Figure 21).

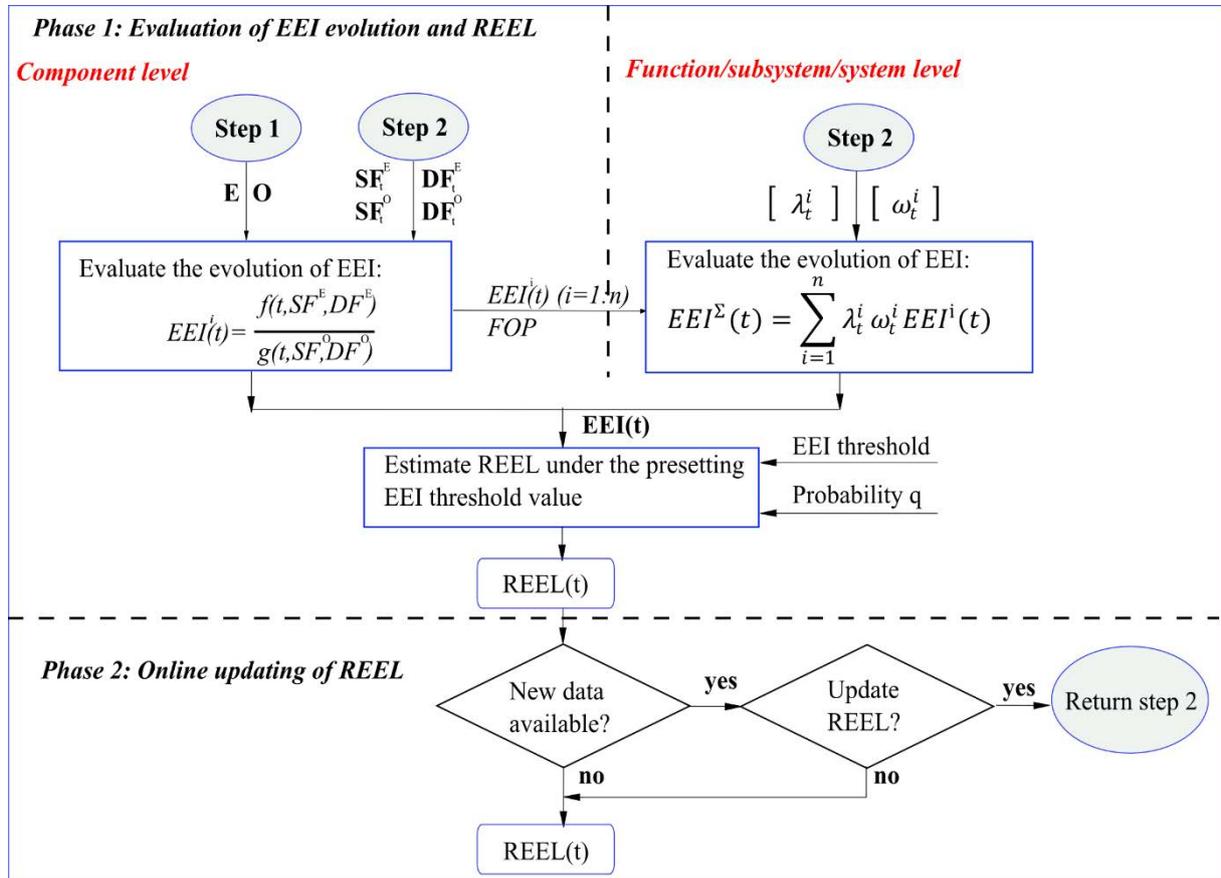


Figure 21. Procedure to evaluate the evolution of EEIs and to estimate the REEL

4.6.1. Phase 1: Evaluation of the evolution of EEI and estimation of REEL

The objective of this phase is to predict the EEI evolution which can help to estimate the REEL at addressed levels. In this context, the achieved energy efficiency model of Step 1 (see section 4.4) under the evolution of all impact factors is used to evaluate the future value of EEIs at the addressed levels.

At the downstream level, the function of the energy consumption and the useful output (results of Step 1) as the function of the predicted evolution of DF and the foreseen value of SF (results of Step 2) are used to evaluate the EEI at any time in the future.

At the higher level, a set of weighting factors under the impact of the forecasted operation profiles and EEI of each component at any time point in the future will be used to evaluate the evolution of EEIs at the function/system level.

The pre-set threshold and the specific context such as the probability q referred to section 0 should be used to estimate the REEL and its variants at both the component and function/system levels, see again Equations (3.11), (3.12) and (3.13).

4.6.2. Phase 2: Online updating of the Remaining Energy-Efficient Lifetime

The aim of the phase 2 is to update the REEL if needed. This means that the estimated REEL should be updated when new data/information on the current state is available. This can be done by turning back to the second step for recalibrating the REEL.

By this step-by-step procedure, the EEI evolution can be predicted to estimate the REEL at the addressed level (component/function/system levels). It is logical that the achieved REEL can provide the useful information for aiding the maintenance decision-making.

4.7. Conclusion

In this chapter, the structure for predicting EEI evolution and the estimation of REEL lead to support the scientific issue No.3, but the methods to implement these evaluations need to be developed.

Through this approach, EEI assessment not only at past and current time but also its prediction in the future is tackled through a generic approach based on existing prognostic models. This generic approach allows to predict the potential evolution of EEI at different level of manufacturing system with a given mission profile using the formulation proposed in chapter 3. Based on the EEI evolution, the REEL can be estimated regarding to the EEI critical threshold which is associated with an energy efficiency property/performance. In fact, the proposed generic approach is divided into three main steps and applicable at different abstraction levels of a manufacturing system. These three steps are:

- *Energy efficiency modeling (Step 1);*
- *Prediction of the potential evolution of impact factors (Step 2);*
- *Evaluating the evolution of EEIs and estimating the REEL (Step 3).*

The proposed generic approach for prognostics of EEI/REEL is applied for a manufacturing platform in the chapter 5.

Chapter 5

Validation of the contributions in the case of TELMA platform

5.1. Introduction

To illustrate and validate the concepts introduced in chapter 3 and the proposed generic approach for prognostics of EEI and REEL (chapter 4), a case study is investigated in this chapter. Indeed, the investigation is brought to a manufacturing platform, called TELMA. Firstly, at component level the impact factors (SF and DF) associated with each component are identified. Since the analytical formulation of EEI is very difficult, some experimentations are carried out to find numerically EEI which is a function of the impact factors. To predict the potential evolution of EEI, the deterioration process of dynamic factors is simulated by a Gamma deterioration process. The prediction result on EEI is then used to estimate the remaining energy-efficient lifetime (REEL). For a higher level (function level), based on EEI at component level, the EEI of the considered “punching” function is determined which can help to estimate the REEL of this function.

5.2. Presentation of TELMA platform

TELMA platform is based on a real industrial application such as steel sheet cutting or metal punching. TELMA is designed for conventional training activities, simulation of online operation on industrial e-services and e-training in the e-Maintenance domains. TELMA platform is based on 4 sub-systems: a bobbin changing, an advance motor-driven system (MD1), an accumulator motor-driven system (MD2) and punching-cutting (Figure 22) [192]–[194]. Each sub-system consists of several components such as gear box, belt tensioner, motor, variable speed drivers (VSDs) (Altivar with and remote I/O modules) and air-compressed valves. An automated control system is fully dedicated to support the offline and online monitoring modes by integrating a monitoring system (sensors, actuators, etc.), Human Machine Interface (HMI) system (control screens, control boards, computers, Web-Cam, etc.), and programmable logic controllers-PLCs (i.e. TSX premium with web interfaces). TELMA consumes mainly electrical energy to form the “simulated” steel strip into shaped steel-sheets, and increasing the number of

formed steel-sheets (considered as the final output of TELMA) obtained per hour corresponding to the main economic productivity performance of TELMA.

TELMA platform is also equipped with software and hardware components to be able to simulate the degradation process (such as deterioration of bearing systems, belts and rollers) and the failure modes like “Belt break”. Indeed, in TELMA platform, it is very difficult to create a real deterioration phenomena or a real failure of the component due to the fact that (i) the operating time of TELMA is not long enough for deterioration/failure appearing and (ii) failure costs are very high (failed components costs). However, to develop experimentation related to maintenance, several specific software and hardware are implemented on the platform (e.g. a degradation software is on a PLC) to simulate the degradation behavior and failure on the system. For example, the belt tensioner is used to simulate the failure event “Belt break” by releasing the belt to the roller. The scenarios of degradation processes or failures are controlled by an automated system (PLC connected to an online monitoring system).

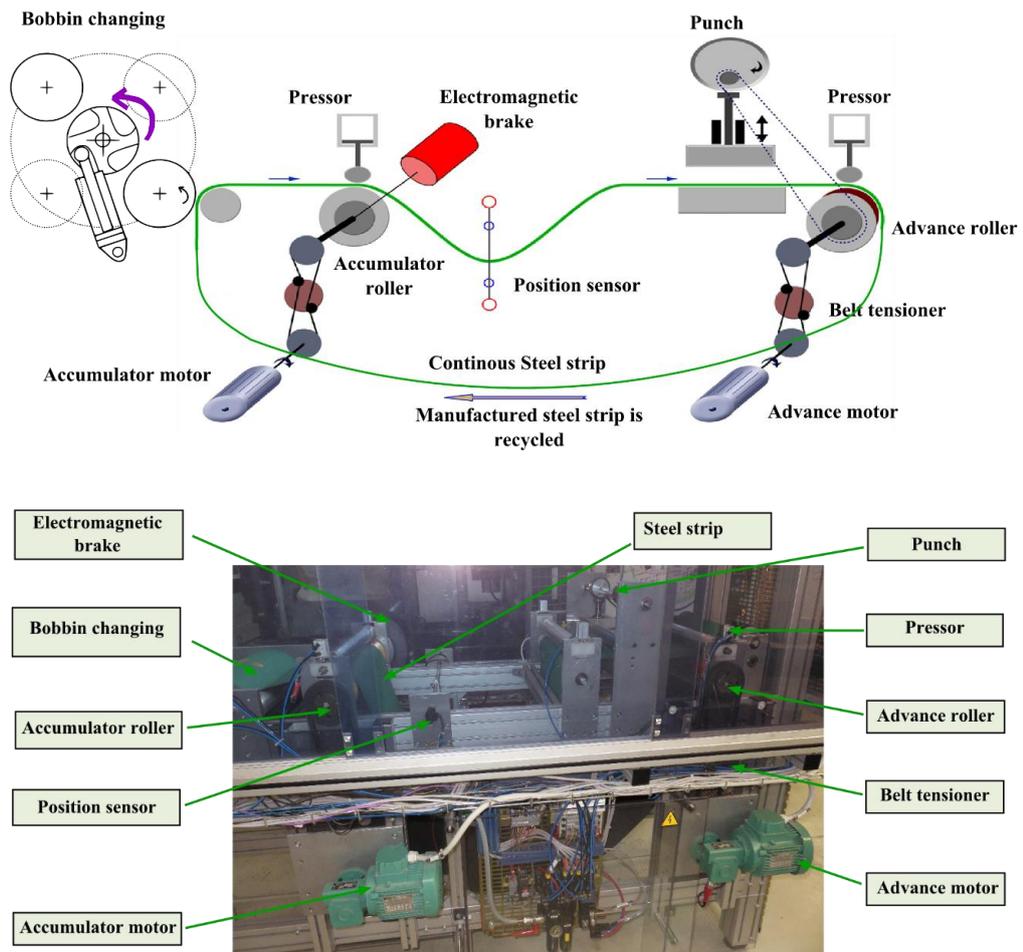


Figure 22. Structure of the platform TELMA

5.2.1 Identification and classification of key components and the function/system

For the validation phase, we are focusing on the “punching” function of TELMA platform. The “punching” function is realized by movement of the mechanical punch press, which is driven by advance motor-driven system MD1, while accumulator motor-driven system MD2 continuously feeds the steel strip to holding position of pressor cylinder. About energy, electricity is directly supply to two Altivar VSDs (provided by Schneider-electric Company) for controlling the speed of two 3-phase induction motors (manufactured by LS Company). The speed setting of these motor driven systems (MD1 and MD2) are related to rotation of the rollers and the productivity of “punching” function of the TELMA.

As key components, we can identify in TELMA platform the followings:

- A bobbin changing
- An advance motor-driven system (MD1) with PLC controller
- An accumulator motor-driven system (MD2) with PLC controller
- Punching-cutting header
- Air-compressor valve and piston
- HMI control panel and online management system

In the frame of EE issue, we just consider the advance motor-driven system (MD1) and the accumulator motor-driven system (MD2) as main energy consumers, the others key components are not taken into account.

5.2.2 Description of the system and experimentation

With regards to this experimental context, we have taken the following assumptions for TELMA.

Bearing is one of the most critical component of a motor-driven system knowing that its working conditions (corrosion, lubrication, etc.) can strongly impact the “bearing frictional losses”[195]. So, we consider here the deterioration of a motor-driven system as assimilated to “bearing deterioration” given that the bearings implemented on TELMA is standard ball bearings (manufactured by SKF with outside diameter $D=35\text{mm}$). Nevertheless, we cannot monitor the real deterioration of bearing (no sensors, no direct inspection possible) but we can use brakes to simulate “bearing deterioration”. Indeed, TELMA platform is equipped with electromagnetic

brakes, which are attached directly on the shaft of the rollers. Simulated degradation level of the bearing is given by the percentage value of brake (from 1 to 100% for simulating the degraded status of bearing). This percentage value of brake is fixed and modified online through a software.

It is generally formulated that the deterioration behavior of bearings can be modeled by a stochastic process [113], [196]. Therefore, a gamma stochastic process is used to simulate the bearing damaging behavior with a shape parameter α and a scale parameter β . For each specific type of bearing, the parameters (α , β) should be modified to adapt with its new deterioration behaviors. So, the experimentation has been done with the same type of bearing and the change of bearing type is not of first interest for us with regards to demonstrate the idea defended (it will not be considered as a main factor in our protocol of validation).

Only “bearing conditions” and production profiles (setting values of productivity or the speed of the motor) are identified as impact factors on TELMA platform, the other operation parameters like temperature, voltage harmonics are seen as unchanged (by lack of instrument and low impact on EE of component). The performances of other elements (VSD, air-compressor valve, etc.) are remaining stable.

No. of test	Speed (rpm)	Deterioration (%)	EC (Wh)
283	1500	82%	355,983
284	1500	84%	364,371
285	1500	86%	369,371
286	1500	88%	370,746
287	1500	90%	380,200
288	1500	92%	391,689
289	1500	94%	399,400
290	1500	96%	407,167
291	1500	98%	408,700
292	1700	0%	209,500
293	1700	2%	210,786
294	1700	4%	212,025
295	1700	6%	212,760
296	1700	8%	213,429
297	1700	10%	215,200
298	1700	12%	216,600
299	1700	14%	216,600
300	1700	16%	216,100
301	1700	18%	217,900
302	1700	20%	219,200
303	1700	22%	221,629
304	1700	24%	222,133
305	1700	26%	224,271

Figure 23. Illustration of data sheet for recorded energy consumption

5.3. Implementation of the generic approach for selection of EEI and related models: architecture definition

On the basis of the assumptions selected, we applied the proposed generic approach for prognostics of EEI and estimation of REEL, to component and function level of TELMA. In that way, each three steps of the approach is detailed below with their application to TELMA.

5.3.1 Step 1: Energy efficiency modeling

As previously mentioned, only the “punching” function level of TELMA is addressed in this study. To support the punching function, it is focusing on the energy efficiency of MD1 and MD2 at the component level and the other auxiliary components are considered as non-consuming energy parts (non-significant consumption). Hence, the scope of this case study is limited to predict the evolution of EEI both at the component level and at the function level. Then the REEL of the function level is estimated.

5.3.1.1 At component level:

It is important to note that, MD1 and MD2 are physically identical but functionally independent. Their speed is controlled by PLC to meet the productivity demand knowing that this demand is materialized through the production plans, of which the productivity of punched steel-sheets are known in advance.

5.3.1.1.1 Phase 1: Specifying the parameters of the energy efficiency model

MD1 and MD2 are considered as single components and transforming electrical energy to mechanical energy for conducting the “punching” function of the TELMA.

- EEIs of MD1 and MD2 can be calculated as the amount of electrical consumption per rotation of the roller. Thus the unit of EEIs for MD1 and MD2 is defined by $\left(\frac{Wh}{round}\right)$.
- Herein, only electrical energy (Wh) is the used energy resource for these motor-driven systems, and the number of rotations (rounds) is considered as the useful output of MD1 and MD2. They are corresponding to the unique unit of EEI $\left(\frac{Wh}{round}\right)$.
- Only bearing conditions (corrosion, lubrication, etc.) and production profiles (setting values of productivity or speed of the motor) are identified as impact factors of MD1 and MD2. In practice, it is important to note that: (i) the effect of the deterioration of the bearings (regardless of the degradation) is mechanically simulated by a force

applied to the shaft of the roller by an electromagnetic brake which is directly attached to the roller; (ii) the power consumption of each motor-driven system mainly depends on the speed (related to the requested output productivity) and the deterioration of the bearing; (iii) the production profile is forecasted from production programs. These impact factors are classified as follows:

- The production profile i.e. the speed at the component level and productivity at the function level is considered as a static factor because a future production program is well known in advance.
- The deterioration of the bearing is random and unknown, so it is considered as a dynamic factor.

5.3.1.1.2 Phase 2: Selection of the prognostic approach for finding EEI function

According to the results of Phase 1, the formulation of the energy consumption and the useful output of MD1 and MD2 should be a function of bearing condition and speed. To select an appropriate prognostics approach to build energy consumption and the useful output models of MD1 and MD2, we consider the following cases (see again Figure 16):

- There is no available physical model for the energy consumption and the useful output of these motor-driven systems i.e. mechanical connection of gear-boxes with motors and the efficiency of belt conveyors, the details technical catalogues and unique physical structure are unknown thus model-based prognostics is not recommended.
- Historical operation data of TELMA has not been recorded but data of TELMA are recordable (sensors and instruments are available). This means that the data-driven prognostics may be used to build energy consumption and the useful output models.
- There is no available expert or engineering of MD1 and MD2. Therefore, the experience-based prognostic is not recommended.

To apply the data-driven prognostic approach for modeling the energy consumption and the useful output of MD1 and MD2, the related energy data of MD1 and MD2 are collected. Because both MD1 and MD2 are identical, an energy audit has firstly been done on the single motor-driven MD1. In fact, the electrical energy is monitored and recorded by two portable power-meters. The rotation of a motor-driven system and its productivity can be recorded by the integrated online monitoring system of the TELMA. Moreover, the electrical consumption of

each motor principally depends on the setting speed and the force of the electromagnetic brake. The power consumption of MD1 is recorded under various values of bearing degradation simulated by the force of the electromagnetic brake and the speed of the motor. Indeed, the degradation level of bearings (D^{MD1}) is adjusted from 0% to 100% (the motor drive is considered as failed when degradation of bearing level reaches 100%) while the output speed of MD1 named S^{MD1} is set from 300 to 1800 r/min.

The recorded electricity consumed (EC) of MD1 is shown in Figure 24 and considered as a function of the motor speed and the deterioration level of the motor.

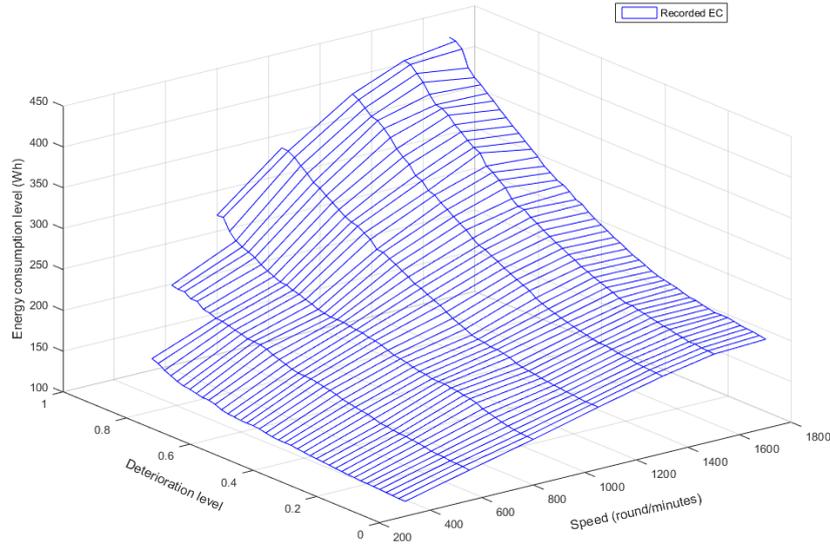


Figure 24. Real energy consumption of MD1 in relationship with speed and deterioration level

Because only the data-driven model is recommended for the motor-driven MD1, the formulation of the energy consumption as a function of speed and bearing deterioration should be fitted by recorded data.

Therefore, a polynomial regression model is used to fit the recorded energy data of MD1 and a multiple regression analysis [197] is applied, i.e.

$$E^{MD1} = \sum_i c_i \prod_j x_j^{k_{i,j}} + \epsilon \quad (5.1)$$

where c_i is the set of coefficients, $x_j = [S^{MD1} \ D^{MD1}]$ is a set of two variables, $k_{i,j}$ is the exponent of each variable and ϵ is the constant. How well the regression model fits the collected data can be presented by the associated coefficient of determination (R^2).

The energy consumption of MD1 has been tested with different degrees of the polynomial. Finally, the energy consumption of MD1 can be estimated by Equation (5.2) with $R^2 = 0,988$. The max and min accuracy values are 8% and -6% respectively.

In this way, the energy consumption of the advance motor drive can be calculated by:

$$\begin{aligned}
 E^{MD1} &= f(S^{MD1}, D^{MD1}) (Wh) \\
 &= \frac{7856}{S^{MD1}} + 19.538 * D^{MD1} + 0.168 * S^{MD1} - 1.19e - 05 * (S^{MD1})^2 * D^{MD1} \\
 &\quad - 4.36e - 05 * (S^{MD1})^2 + 0.011 * S^{MD1} * D^{MD1} + 0.104 * S^{MD1} * (D^{MD1})^2 \\
 &\quad + 1.8e - 05 * (S^{MD1})^2 * (D^{MD1})^2 + 44.91(Wh)
 \end{aligned} \tag{5.2}$$

where S^{MD1} and D^{MD1} represent the output speed and the bearing deterioration level of the advance motor-driven MD1.

The difference between the measured and calculated energy consumption of MD1 is shown in Figure 25.

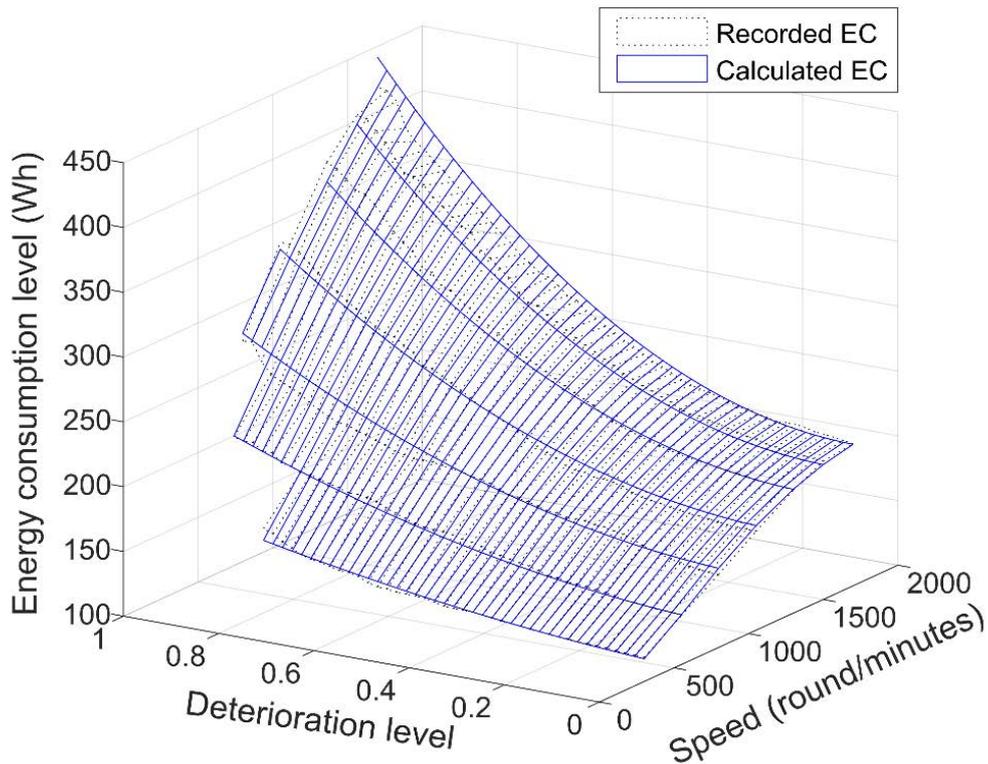


Figure 25. Calculated energy consumption of MD1 in relationship with speed and deterioration level

In order to ensure the synchronized speed between the two motors, the running speed is controlled by PLC controllers. To maintain the useful output of system, the speed of roller may be increased to perform more operation to complement the waste output to maintain the productivity of punching function, for example, the slip between the roller the steel strip will impact the number of steel sheet can be punched. The controller can impact the real operating speed of motor driving system as following:

$$S^{MD1} = S_0^{MD1} + \theta \left(\frac{round}{minutes} \right), \quad (5.3)$$

Where θ presents the impact of controller accuracy to the operation speed of motor driven, θ can be seen as static impact factor. It is assumed that θ is subject to a degradation with $\theta = k * t$ with k is a coefficient. In this study we take $k = 7$ for current state of controller of TELMA.

The output production capacity O^{MD1} during any period of time unit (from t to $(t+1)$) is calculated as function of the setting speed S_0^{MD1} with rotation of roller seen as unit of output of MD1. The ratio between rotation of motor and rotation of roller in the ideal case is fixed by the ratio of gearbox and bell-driver system. In case of TELMA, we can used this ratio to calculate output production capacity O^{MD1} from the setting speed S_0^{MD1} for each one hour of operation:

$$O^{MD1} = 60 * \frac{S_0^{MD1}}{2500} (round), \quad (5.4)$$

where S_0^{MD1} is setting speed of MD1 for each production mode.

Based on the results obtained by Equations (3.1), (5.2) and (5.4), we can use the following equation to calculate EEI of MD1:

$$\begin{aligned} EEI^{MD1} &= \frac{E^{MD1}}{O^{MD1}} (Wh/round) \\ &= \frac{32.7e + 04}{S^{MD1} * S_0^{MD1}} + \frac{814 * D^{MD1}}{S_0^{MD1}} + 7 * \frac{S^{MD1}}{S_0^{MD1}} \\ &\quad - 49.59e - 05 * \frac{(S^{MD1})^2 * D^{MD1}}{S_0^{MD1}} - 18.16e - 04 * \frac{(S^{MD1})^2}{S_0^{MD1}} \\ &\quad + 0.458 * \frac{S^{MD1} * D^{MD1}}{S_0^{MD1}} + 4.33 * \frac{S^{MD1} * (D^{MD1})^2}{S_0^{MD1}} \\ &\quad + 75e - 05 * \frac{(S^{MD1})^2 * (D^{MD1})^2}{S_0^{MD1}} + \frac{1871}{S_0^{MD1}} (Wh/round) \end{aligned} \quad (5.5)$$

EEI of MD1 in relationship with the output speed and the deterioration level according to Equation (5.5) is shown in Figure 26. The higher operating-speed of motors and/or the higher level of bearing deterioration, the higher values of EEI can be calculated/recorded. The calculated EEI values and recorded EEI values for MD1 are very close; it means that the EEI model can be accepted with the sufficient accuracy at function level.

As the two motors are identical, the energy consumption, the useful output and EEI of MD2 can be calculated by equations:

$$\begin{aligned}
 E^{MD2} &= f(S^{MD2}, D^{MD2}) (Wh) \\
 &= \frac{7856}{S^{MD2}} + 19.538 * D^{MD2} + 0.168 * S^{MD2} - 1.19e - 05 * (S^{MD2})^2 * D^{MD2} \\
 &\quad - 4.36e - 05 * (S^{MD2})^2 + 0.011 * S^{MD2} * D^{MD2} + 0.104 * S^{MD2} * (D^{MD2})^2 \\
 &\quad + 1.8e - 05 * (S^{MD2})^2 * (D^{MD2})^2 + 44.91(Wh)
 \end{aligned} \tag{5.6}$$

$$S^{MD2} = S_0^{MD2} + \theta \left(\frac{\text{round}}{\text{minutes}} \right), \tag{5.7}$$

$$\begin{aligned}
 EEI^{MD2} &= \frac{E^{MD2}}{O^{MD2}} (Wh/round) \\
 &= \frac{32.7e + 04}{S^{MD2} * S_0^{MD2}} + \frac{814 * D^{MD2}}{S_0^{MD2}} + 7 * \frac{S^{MD2}}{S_0^{MD2}} \\
 &\quad - 49.59e - 05 * \frac{(S^{MD2})^2 * D^{MD2}}{S_0^{MD2}} - 18.16e - 04 * \frac{(S^{MD2})^2}{S_0^{MD2}} \\
 &\quad + 0.458 * \frac{S^{MD2} * D^{MD2}}{S_0^{MD2}} + 4.33 * \frac{S^{MD1} * (D^{MD1})^2}{S_0^{MD2}} \\
 &\quad + 75e - 05 * \frac{(S^{MD2})^2 * (D^{MD2})^2}{S_0^{MD2}} + \frac{1871}{S_0^{MD2}} (Wh/round)
 \end{aligned} \tag{5.8}$$

With S^{MD2} and D^{MD2} represent the output speed and the bearing deterioration level of accumulator motor drive MD2.

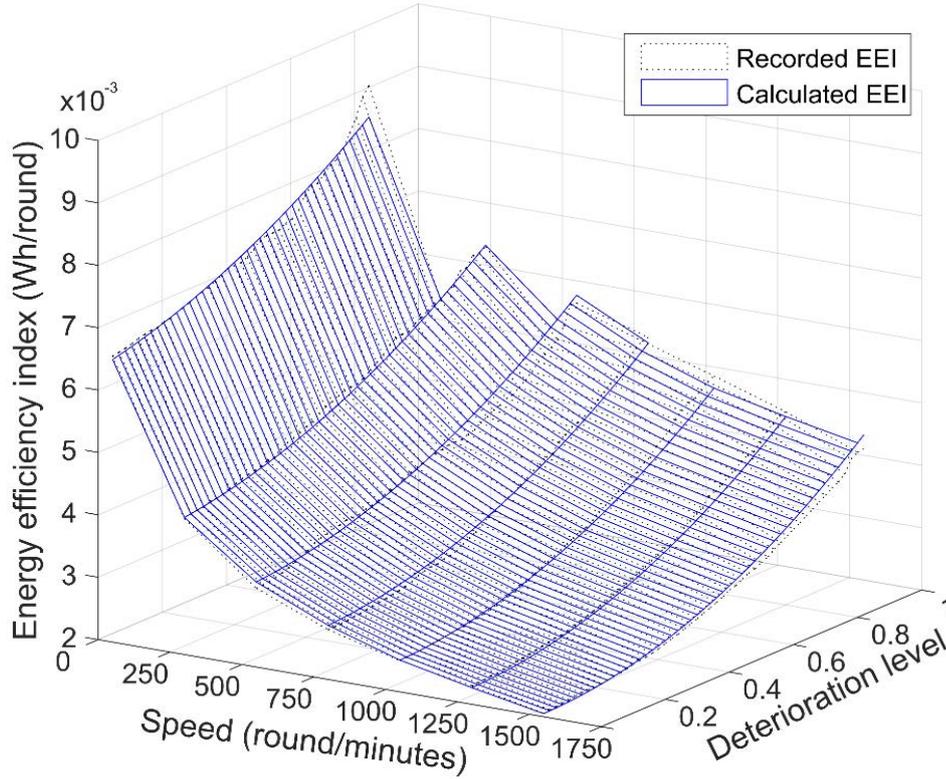


Figure 26. EEI of MD1 as a function of speed and bearing deterioration at the component level

5.3.1.2 At function level:

Only “punching” function is focused at function level of TELMA (see section 5.1). This function is supported by the two components MD1 and MD2 to manufacture punched product. Thus, EEI at the function level is defined as the electrical energy consumption per product ($\frac{Wh}{product}$). The physical useful output at the function level is the number of products (cutting steel sheets).

All the electrical energy which consumed by the two components MD1 and MD2 is to support only the punching function. Thus, the total energy consumption E^Σ at the function level is the total energy consumption of both individual components MD1 and MD2, and can be calculated as:

$$E^\Sigma = E^{MD1} + E^{MD2}(Wh) \tag{5.9}$$

This relationship is obtained from Equation (3.9):

$$E^\Sigma = \sum_{i=1}^2 \lambda^{MDi} E^{MDi} = \lambda^{MD1} E^{MD1} + \lambda^{MD2} E^{MD2} \tag{5.10}$$

By comparing the Equation (5.9) and (5.10) we can identify the energy weighting factors $[\lambda^{MD1} \ \lambda^{MD2}] = [1 \ 1]$.

In order to consider the output of the punching function as the production rate that is directly related to the rotation of MD1 and MD2, it is important to note that to produce one product, the rollers have to turn 25 rounds (this value is fixed according to the permanent physical connection between roller and punch). Hence, the output weighting factors of separated MD1 and MD2 at the function/system level can be expressed as follows:

$$[\omega^{MD1} \quad \omega^{MD2}] = \left[\frac{O^{MD1}}{O^{\Sigma}} \quad \frac{O^{MD2}}{O^{\Sigma}} \right] = \left[\frac{25}{1} \quad \frac{25}{1} \right] \quad (5.11)$$

The EEI of the considered “punching” function of the TELMA, EEI^{Σ} , can be calculated by:

$$EEI^{\Sigma} = \sum_{i=1}^2 \lambda^{MDi} \omega^{MDi} EEI^{MDi} = 1 * 25 * EEI^{MD1} + 1 * 25 * EEI^{MD2} \left(\frac{Wh}{product} \right) \quad (5.12)$$

5.3.2 Step 2: Prediction of the evolution of impact factors

From the identified impact factors of step 1 (section 4.2), the future operating conditions like bearing deterioration levels, speed of motors and production plan should be forecasted.

5.3.2.1 At component level

On TELMA, a production program that is considered as a static factor and seen in advance by using Markov processes is forecasted as shown in Figure 27.a. It is assumed that the production schedule does not impact the deterioration process of two motors and that the bearing deterioration behavior of MD1 and MD2 depends only on the time. A gamma stochastic process is used to simulate the bearing damaging behavior of MD1 and MD2 [113]. Two parameters $\alpha > 0$ and $\beta > 0$ are taken and Gamma function $\Gamma(\alpha)$ is defined by:

$$\Gamma(\alpha) = \int_0^{\infty} u^{\alpha-1} e^{-u} du \quad (5.13)$$

During $(T_{i-1} - t)$ period of time unit, the increment in the deterioration level of the bearing $x = (D(t) - D(T_{i-1}))$ follows Gamma probability density with the shape parameter $\alpha(t - T_{i-1})$ and the scale parameter β as:

$$f_{\alpha(t-T)(x)} = \frac{\beta}{\Gamma(\alpha(t-T_{i-1}))} (\beta x)^{\alpha(t-T_{i-1})-1} (e)^{-\beta x} \quad (5.14)$$

The deterioration speed and its variance are $k = \alpha/\beta$ and $Var[x] = \alpha/\beta^2$ respectively. In case of real data of bearings are recordable or available, the parameters (α, β) of the bearing deterioration model can be identified [196]. The parameters associated with the Gamma deterioration model (based on the data of deterioration behaviors of MD1 and MD2) are presented in Table 6. Each motor-driven system is considered failed when the deterioration level reaches the 100% level.

Table 6. Parameters (α, β) of the bearing deterioration model of MD1 and MD2

Component	α	β	L
Motor 1	0.1	0.1	100
Motor 2	0.2	0.1	100

The deterioration evolution of the two motors is illustrated in Figure 27.b. It underlines that the bearing evolution of MD1 and MD2 are noticeably different.

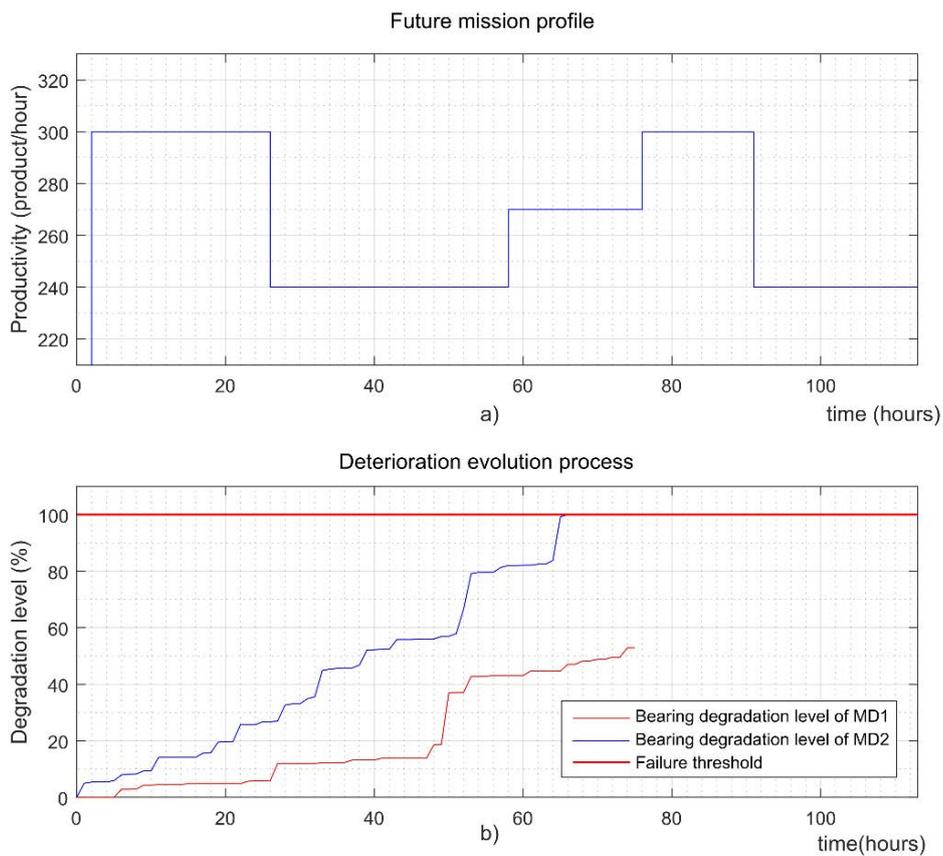


Figure 27. A forecasted mission profile (a) and the bearing deterioration evolution of two motor-driven systems MD1 and MD2 (b)

5.3.2.2 At the function level:

As the configuration and structure of TELMA are fixed during operation plans, the energy flow and production structure are unchanged. Therefore, the weighting factors of both the two motor-driven MD1 and MD2 are fixed and considered as: $[\lambda_t^{MD1} \ \lambda_t^{MD2}] = [1 \ 1]$ and $[\omega_t^{MD1} \ \omega_t^{MD2}] = [25 \ 25]$. In this case, only the evolution of EEIs of two components MD1

and MD2 impact the changing of EEI value at function level $EEI^{\Sigma}(t)$. This leads to a final formulation of EEI at the function level that can be determined by the following equation:

$$\begin{aligned}
 EEI^{\Sigma}(t) &= \sum_{i=1}^2 \lambda_t^{MDi} \omega_t^{MDi} E^{MDi}(t) \\
 &= 1 * 25 * EEI^{MD1}(t) + 1 * 25 * EEI^{MD2}(t) \left(\frac{Wh}{product} \right)
 \end{aligned}
 \tag{5.15}$$

Because the evolution of EEI for each motor-driven is different according to their characteristic (deterioration speed, controller accuracy, etc.), the distribution of EEI at “punching” function level can be totally different.

5.3.3 Step 3: Evaluation of the potential evolution of EEI and estimation of REEL

Based on the simulated productivity (see again Figure 27.a) and bearing deterioration evolution, which are predicted in Step 2 (see section 4.3.2), EEI of MD1 and MD2 at the component and function levels of TELMA can be estimated at any time point. EEI evolution at the component/function levels of the platform TELMA is shown in Figure 28.

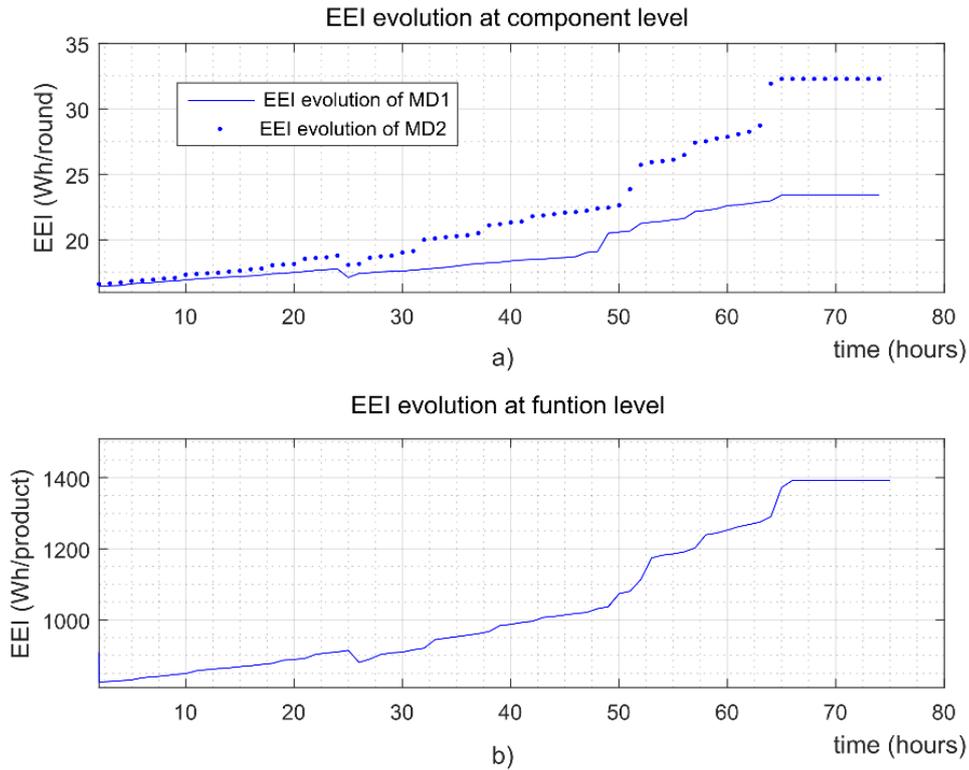


Figure 28. Evolution of EEI at the component level (a) and at the function level (b)

A limit value $EEI_{Threshold} = 1030$ (Wh/product) is given in advance as a threshold value at the function level. TELMA platform is seen to work in the energy inefficient zone when its EEI

crosses over this $EEI_{Threshold}$. This means that TELMA may be available to perform “punching” function, but it consumes more energy than usual. In this sense, it is interesting to know when the platform will lose its energy efficiency property. Figure 29.a illustrates the predicted evolution of EEI and Figure 29.b represents distribution of the REEL at the function level by using 20000 simulated paths of the evolution of EEI^2 (at function level) that takes into account EEI evolution of the two motor-drives MD1 and MD2. This figure draws a histogram of values in REEL data using the number of bins equal to the square root of the number of elements in data and fits a normal density function. It should be noted that, according to this figure, several values of the REEL can be determined according to its specific definition. For example, a considerable amount of the MREEL = 39 hours can be clearly determined.

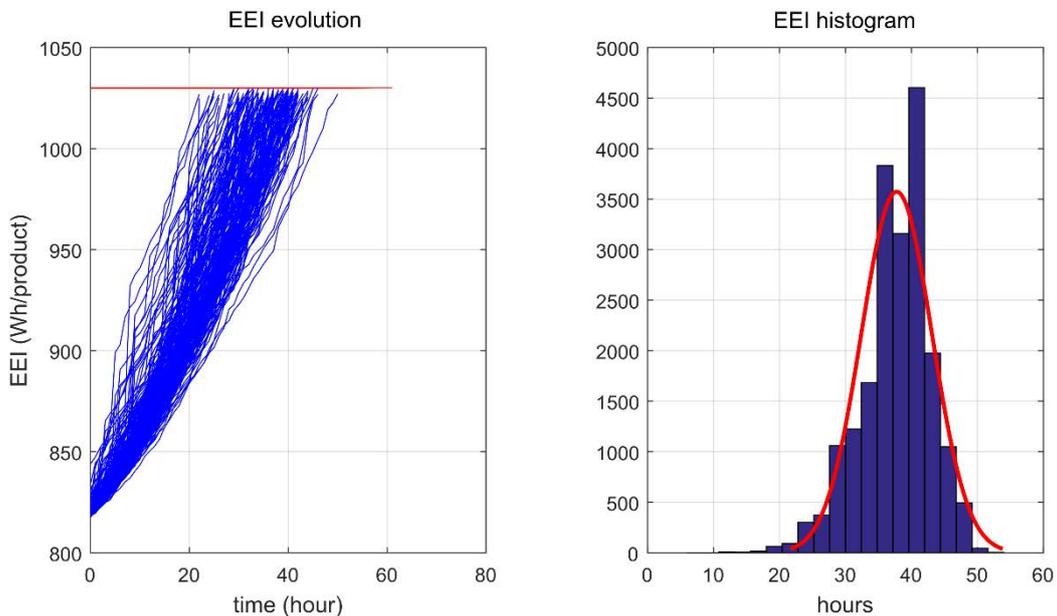


Figure 29. Distribution of the REEL at $EEI_{Threshold} = 1030 \left(\frac{\text{Wh}}{\text{product}} \right)$

By this step-by-step procedure, the EEI evolution can be predicted to estimate the REEL at the function level. It is logical that the achieved REEL can provide the useful information for aiding the maintenance decision-making.

5.4. Conclusion

This chapter has tackled the first validation step of the scientific contributions proposed in chapter 3 and 4, by illustrating them to TELMA platform at both component and function level. The two electrical motor driven are considered at component level and only punching function is investigated at the function level [198]. For each motor, several

experimentations on the energy consumption as a function of the production plan (static impact factor) and the deterioration state of bearing (dynamic impact factor) are carried out. Based on the recorded data, an EEI model (including two formalization of energy consumption and output) is provided at both component and function level. For the prognostic implementation for EEI/REEL prediction, the evolution of the bearing is described by a Gamma process. The achieved results demonstrate that the EEI evolution can be predicted both at the component level and at the function level for specific experiment.

The study developed in this chapter highlights the potential achievement of our proposals and shows the added value of the proposed EEI and REEL concept.

Chapter 6

Use of EE for CBM maintenance decision-making

6.1. Introduction

This chapter describes our contribution on the use of EE for condition-based maintenance which is the scientific issue n°4 pointed out in chapter 2. Firstly, a qualitative study on the use of EEI for decision-making is investigated. Then a detailed development of EEI for condition-based maintenance is presented. In fact, the main idea is to use EEI as the decision indicator for selecting a component or a group of several components to be preventively maintained. Two kinds of preventive decision rules are proposed. A cost model is then proposed for finding the optimal decision parameters. Moreover, a classical CBM, in which the preventive decision-making is based on a conventional degradation indicator, is also extended by considering not only the maintenance cost but also the energy cost in the way to compare the proposed EEI-based CBM approach with the conventional (extended) one. The comparison step is developed on the case study of TELMA platform allowing to assess the impact of EEI on the existing CBM policy and to conclude on the interest of EEI for CBM decision-making in terms of cost and efficiency.

6.2. General discussions on EEI indicator for decision-making

Before using EEI as a main indicator in CBM maintenance decision-making, we want just to underline several principal characteristics of EEI (in addition to the discussion already done in chapter 2).

EEI is a universal indicator for different decision-making levels

Measuring business performance is the top priority for most of industrial stakeholders. The higher level of decision-making is, the more universal decision-indicators should be. It means that decisional indicators can provide the economical information for higher decision-making levels. In CBM framework, conventional degradation indicators such as crack, noise, etc. are not easy to transform to financial indicators while EEI can be easily transferred to the monetary. EEI threshold has to be defined to fulfil specific business goals and objectives such as supporting

environment certificate, eco-maintenance – “green production” [199]. It can be directly linked to the overall goals of the company (especially at strategic level).

EEI provides a clear vision for decision-makers:

Firstly, energy efficiency is supported by various conceptual/theory framework (codes, standard, guideline, etc.) [47], [57], [150]. [158], [200]. [16], [87], [116]. These proposed works help to measure, monitoring and evaluate EE performance at different application domains in comparison with lack of framework for conventional indicators.

Secondly, EEI is understandable for any decision-maker while most of conventional indicators are quite complicated in representing the health status of component/system. The EEI value can be measurable by, for example, implementing energy efficiency audit. Technical operators usually know what impact factors should be measured (related to energy consumption, output), how it's being calculated and finally what actions can positively impact EEI [201].

Low inspection cost:

In reality, energy management systems (EMS) are implemented in almost industrial system to control and regulate the machines in order to improve its energy efficiency performance [202]–[204]. Therefore, EEI can be monitored with an inspection cost [193]. While to monitor conventional deterioration indicators, additional measurements and many computations may be required [97]. As a consequence, monitoring/acquiring the data of conventional indicators may be more complicated, expensive, and impractical for actual application [205], [206]. Furthermore, physical inspection duration may be longer than EEI inspection duration. This may lead to an addition consequence such as low production capacity, waste labor forces. Moreover, under the development of IT technology, the energy data can be continuously collected over time [207], [208]. This can help to optimally update online the maintenance decision-making process adapting with real operation situations.

6.3.EEI-based CBM maintenance

It is assumed, in this CBM study, that both corrective and preventive maintenance are possible for each component and these maintenance actions can bring the maintained component to be a new one (replacement action). We also suppose that the maintenance duration can be neglected.

6.3.1. Maintenance decision rules

It is assumed that EEI of each component is monitored at each regular time point $T_i = i * \Delta T$ (ΔT is a decision parameter to be optimized; $i=1,2,\dots$). Each energy efficiency inspection costs C_{in}^E .

Between two consecutive inspection times, if component j fails, a corrective maintenance action is performed at the next inspection date with a corrective maintenance cost C_c^j . If the failure of component j leads to a shutdown of the function/system, a downtime cost $C_d \cdot d_i(t)$ (with C_d is the downtime cost rate and d_i is the downtime duration between $[T_{i-1}, T_i]$) is added.

For preventive maintenance operations, we consider herein two main preventive maintenance policies: individual maintenance and grouping maintenance. This consideration leads to a first part of the scientific issue n°4 which is related to using EEI value as condition of CBM strategy.

6.3.1.1. Individual maintenance policy:

At each regular time point T_i , a preventive maintenance on component j is triggered if its EEI value monitored, $EEI_{T_i}^j$, is higher than a threshold denoted $EEI_{Pre_threshold}^j$ which is also a decision parameter to be optimized. In that way, the decision rules for each component at each regular time point is the following:

- if $EEI_{T_i}^j < EEI_{Pre_threshold}^j$ then no maintenance action is performed;
- if $EEI_{T_i}^j \geq EEI_{Pre_threshold}^j$ then a preventive maintenance action on component j is performed. A preventive cost C_p^j has to be paid.

The illustration of maintenance decision rules is shown in Figure 30.

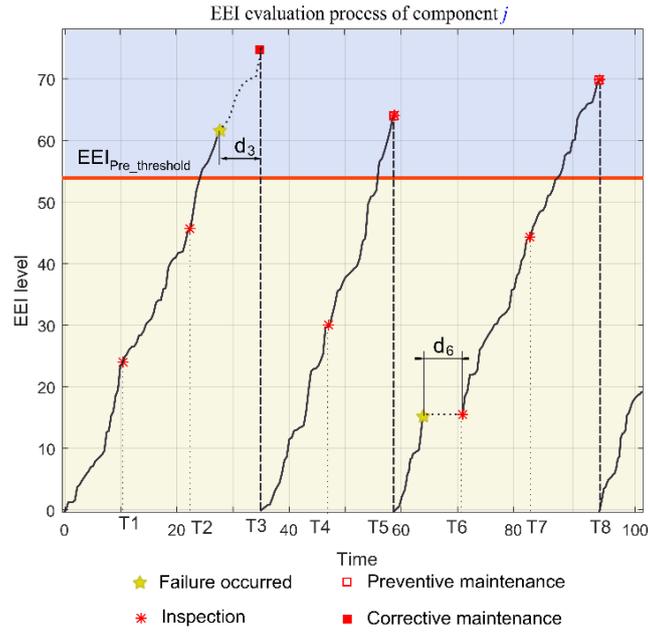


Figure 30. Illustration of EEl evolution of one component and maintenance decision rules

If a function/system is composed of N components, there are $N+1$ decision parameters to be optimized.

6.3.1.2. Grouping maintenance policy:

The main idea of grouping policy [209] is at each regular time point T_i , EEl of the considered function/system, denoted $EEI_{T_i}^{\Sigma}$, is calculated based on the EEl's at component level, the preventive decision rules are the following:

- if $EEI_{T_i}^{\Sigma} \leq EEI_{Pre_threshold}^{\Sigma}$ with $EEI_{Pre_threshold}^{\Sigma}$ is a decision parameter to be optimized preventively, no maintenance action is then carried out;
- if $EEI_{T_i}^{\Sigma} > EEI_{Pre_threshold}^{\Sigma}$, preventive maintenance on a group of several components is needed. In this case, a question arising is how to select the group of several components? In fact, there are different kinds of decision rules for selecting a group of several components to be preventively replaced. The simplest way is that a group of several components is considered as admissible one if the replacement of all group's components can reduce the EEl indicator of the function/system to be lower than the threshold $EEI_{Pre_threshold}^{\Sigma}$. Based on the admissible groups of components, the optimal group is the one with the minimum maintenance cost.

The illustration of maintenance decision rules is shown in Figure 31.

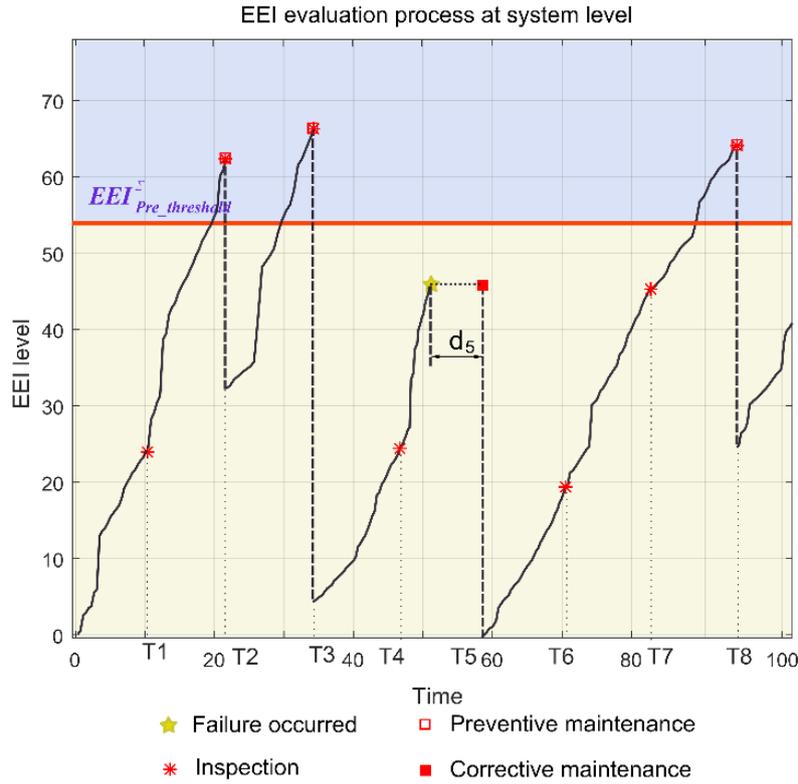


Figure 31. Illustration of EEl evolution of system and maintenance decision rules

According to the group maintenance policy, only two decision parameters are required

6.3.1.3. Cost model

To find the optimal decision parameters, cost is used as a main criterion. In that way, the long-run expected cost per useful output unit, is used. The following development is applied for both the individual maintenance and grouping maintenance policies.

The cumulative total cost for the period (0-t] is expressed as:

$$TotalC^t = MC^t + EC^t \tag{6.1}$$

where:

- MC^t is the cumulative maintenance cost which can be calculated by

$$MC^t = CI^t + CP^t + CC^t + CD^t \tag{6.2}$$

where: CI^t , CP^t , CC^t and CD^t are respectively the costs associated with to EEl inspection, preventive maintenance, corrective maintenance and downtime duration during the period (0-t].

- EC^t is the cumulative energy cost and can be calculated as

$$EC^t = Ep \cdot \int_0^t \sum_{i=1}^N E^i(x) dx \quad (6.3)$$

With Ep represents the energy price and $E^i(x)$ is the energy consumption during one time unit (from $(x-1)$ to x) of component j . $E^i(t)$ depends not only on the state/deterioration level of component j but also on the other impact factors (such as product capacity, waste rate).

$$E^j(t) = f(t, X_t^j, x(t)) \quad (6.4)$$

Where X_t^j is the state/degradation level of component j and $x(t)$ is the set of impact factors during one time unit (from t to $(t+1)$). It is important to recall that component j is considered as failed if its deterioration level is not lower than a critical threshold: $X_t^j \geq L^j$.

The cumulative useful output during the period $(0, t]$ is written as:

$$\phi(t) = \int_0^t O(x) dx \quad (6.5)$$

The long run global cost per useful output unit is the following:

$$CO = \lim_{t \rightarrow \infty} \frac{TotalC^t}{\phi(t)} \quad (6.6)$$

By using the renewal theory [210], we obtain:

$$CO = \frac{E[TotalC^H]}{E[\phi(H)]} \quad (6.7)$$

with H is the first replacement date. Stochastic Monte Carlo simulation (on MATLAB tools) is used to evaluate this cost criterion. To do so, for each value of decision parameters, the corresponding total cost per useful output unit is calculated. To ensure that the convergence of maintenance cost rate is reached, a large number of simulation realizations (each realization simulates one life cycle of the system) must be done. The optimal value of the decision parameters are given when the total cost per useful output searches its minimum value [211].

6.3.2. Extension of a classical CBM policy

To highlight the performance of the proposed EEI-CBM based maintenance, a classical CBM, namely (M,T) policy in which a conventional deterioration is used as a main decisional

indicator is extended by integrating the energy consumption cost. The comparison between the extended (M,T) CBM and EEI-based CBM tackles the second part of the scientific issue n°4 which related to assess the benefits of EEI-based CBM strategy.

6.3.2.1. Maintenance decision rules

It is assumed that the deterioration level of each component is inspected at regular each regular time point $T_i = i * \Delta T$ (ΔT is a decision parameter to be optimized; $i=1,2,\dots$). Each deterioration inspection costs C_{in}^D with ($C_{in}^D \geq C_{in}^E$).

Between two consecutive inspection times, if component j fails, a corrective maintenance action is performed at the next inspection date with a corrective maintenance cost C_c^j . If the failure of component j leads to a shutdown of the function/system, a downtime cost $C_d \cdot d_i(t)$ (with C_d is the downtime cost rate and d_i is the downtime duration between $[T_{i-1}, T_i]$) is added.

Concerning preventive maintenance, unlike EEI indicator, the deterioration indicator can be only defined at component level, as a consequence, a unique main maintenance policy is herein considered: individual maintenance. The decision rules for component j are the following:

- if $X_{T_i}^j < M^j$ then no maintenance action is performed. M^j is the preventive threshold to be optimized;
- if $X_{T_i}^j \geq M^j$ then a preventive maintenance action on component j is performed. A preventive cost C_p^j has to be paid.

Figure 32 presents the behavior of single component with its evolution of deterioration level with maintenance actions.

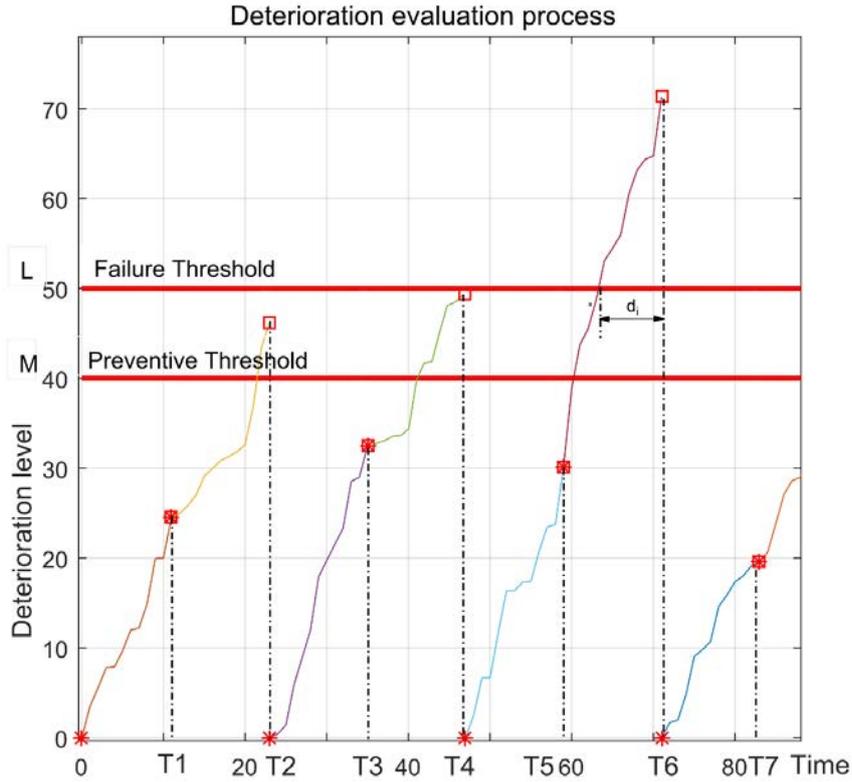


Figure 32. Behaviour of the maintained component under the (M,T) policy

According to the policy, there are $N+1$ decision parameters ($\Delta T, M^1, M^2, \dots, M^N$) to be optimized.

6.3.2.2. Cost model with consideration of energy consumption cost

By considering the energy cost in the total cost to operate the industrial system.

The long run global cost per useful output unit is the following:

$$CO = \lim_{t \rightarrow \infty} \frac{TotalC^t}{O(t)} \quad (6.8)$$

with:

$$TotalC^t = MC^t + EC^t \quad (6.9)$$

where:

- MC^t is the cumulative maintenance cost which can be calculated by

$$MC^t = CI^t + CP^t + CC^t + CD^t \quad (6.10)$$

where: CI^t , CP^t , CC^t and CD^t are respectively the costs related to degradation inspection, preventive maintenance, corrective maintenance and downtime duration during the period $(0-t]$.

- EC^t is the cumulative energy cost and can be calculated as

$$EC^t = Ep. \int_0^t \sum_{i=1}^N E^j(x) dx \quad (6.11)$$

The cumulative useful output during the period $(0 t]$ is written as:

$$\phi(t) = \int_0^t O(x)dx \quad (6.12)$$

The long run global cost per useful output unit is the following:

$$CO = \lim_{t \rightarrow \infty} \frac{TotalC^t}{\phi(t)} \quad (6.13)$$

By using the renewal theory [210], we obtain:

$$CO = \frac{E[TotalC^H]}{E[\phi(H)]} \quad (6.14)$$

Stochastic Monte Carlo simulation is used to evaluate this cost criterion. To do so, for each value of decision parameters $(\Delta T, M^1, M^2, \dots, M^N)$ the corresponding cost per useful output unit is calculated.

The optimal value of the inspection period and the preventive thresholds are given by minimizing the total cost per useful output.

6.4.Implementation platform TELMA

The proposed EE-based CBM maintenance policy is applied on TELMA platform dedicated to e-maintenance (as described in section 5.2). The proposed EE-based CBM maintenance and the (M,T) policy are applied for only one motor-driven MD1. The speed of MD1 is set to $S_0^{MD1} = 300$ (rpm). The data concerning the deterioration behavior and the energy consumption of MD1 discussed in Section 5.2 is reconsidered. Table 7 reports the cost data (computed in cost unit – CU).

Table 7. Energy and maintenance simulation parameter

E_p	C_p	C_c	C_d	c_{in}^E	c_{in}^D
0.025 (CU/Wh)	100 (CU)	150 (CU)	100 (CU)	1 (CU)	10 (CU)

6.4.1. Maintenance optimization for MD1

6.4.1.1. *EEI-based CBM maintenance*

Figure 33 shows the surface of cost rate of the EEI-based policy as a function of the decision parameters ($\Delta T, EEI_{Pre_threshold}$). The optimum value of the decision parameters are $EEI_{Pre_threshold}^* = 25$ (Wh/round) and $\Delta T^* = 9$ (hours) with the minimum global cost per product unit $CO^*(.) = 0.74$ (CU/round).

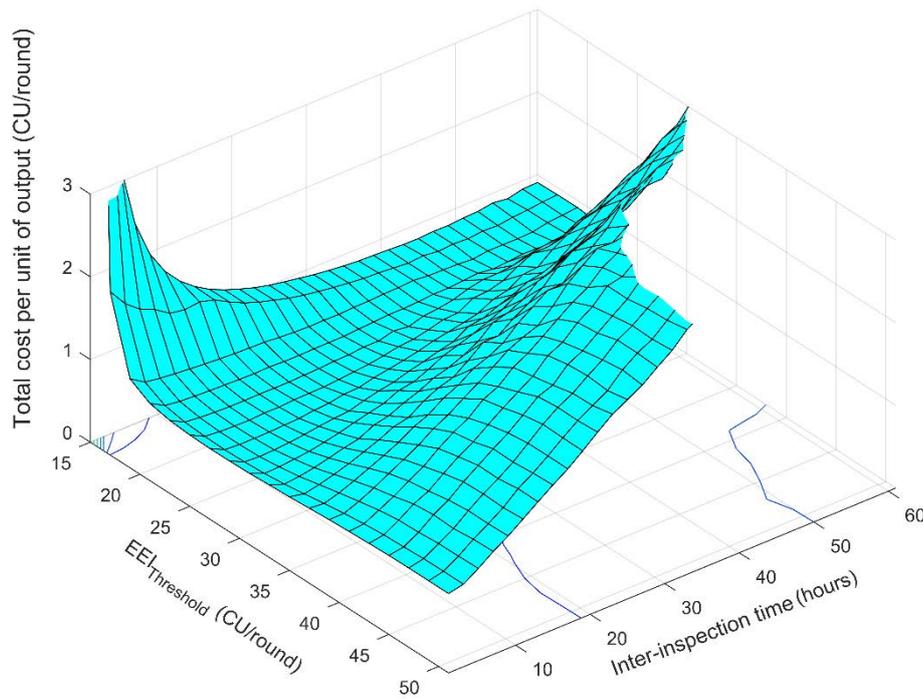


Figure 33. Cost rate surface of the EEI-based CBM maintenance

6.4.1.2. *(M,T) maintenance policy*

In the same manner, the total cost including maintenance and energy cost per product unit is calculated for each set of the decision parameters ($\Delta T, M$). Figure 34 shows the shape of the cost rate of the (M,T)-based CBM policy for MD1.

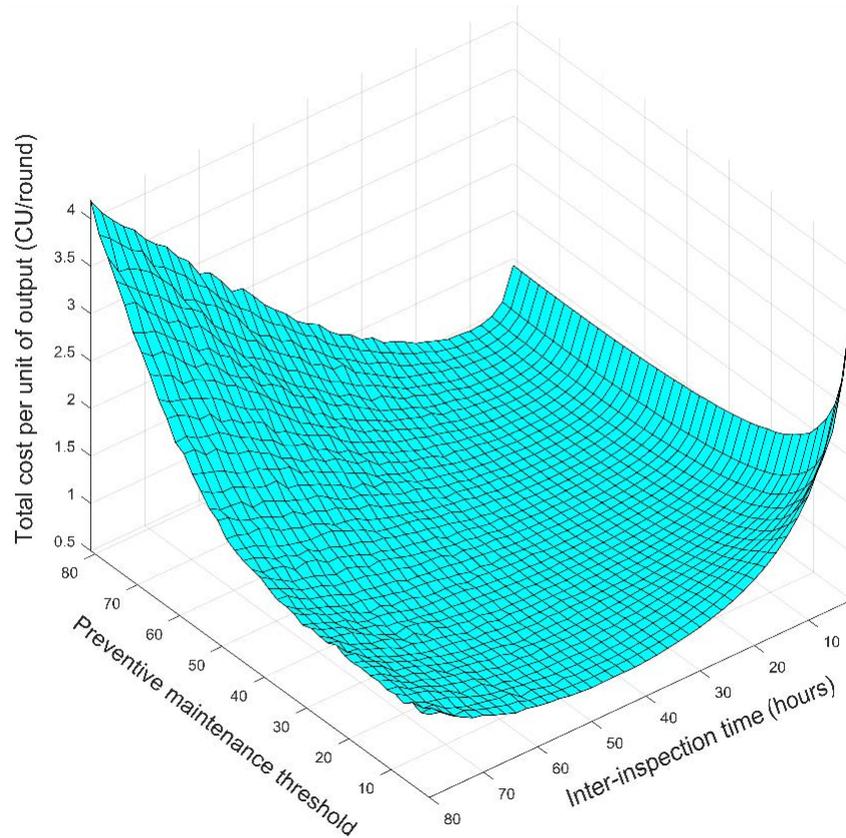


Figure 34. Cost rate surface of the (M,T)-based CBM policy

The optimal decision parameters are the maintenance threshold $M^* = 43$ and inspection period $\Delta T^* = 24$ (hours) with $CO^*(.) = 0.81$ (CU/round). When compared to the proposed EEI-based policy, the (M,T) maintenance policy leads to a higher cost rate. This can be explained by the fact that the inspection cost for EEI is lower than the inspection cost of bearing deterioration indicator and more importantly the potential evolution of EEI vary less than the bearing deterioration indicator do. This leads to a higher performance of the decision-making based on the EEI. As example, Figure 35.a shows the distribution of EEI and the bearing deterioration indicator at preventive maintenance time which is based on EEI level ($EEI_{Pre_threshold} = 25$ (Wh/round)). When the preventive maintenance decision is based on the bearing deterioration level ($M = 43$), the distribution of EEI and the bearing deterioration indicator are shown in Figure 35.b. It is found that the variation of EEI is less than that of the bearing deterioration indicator.

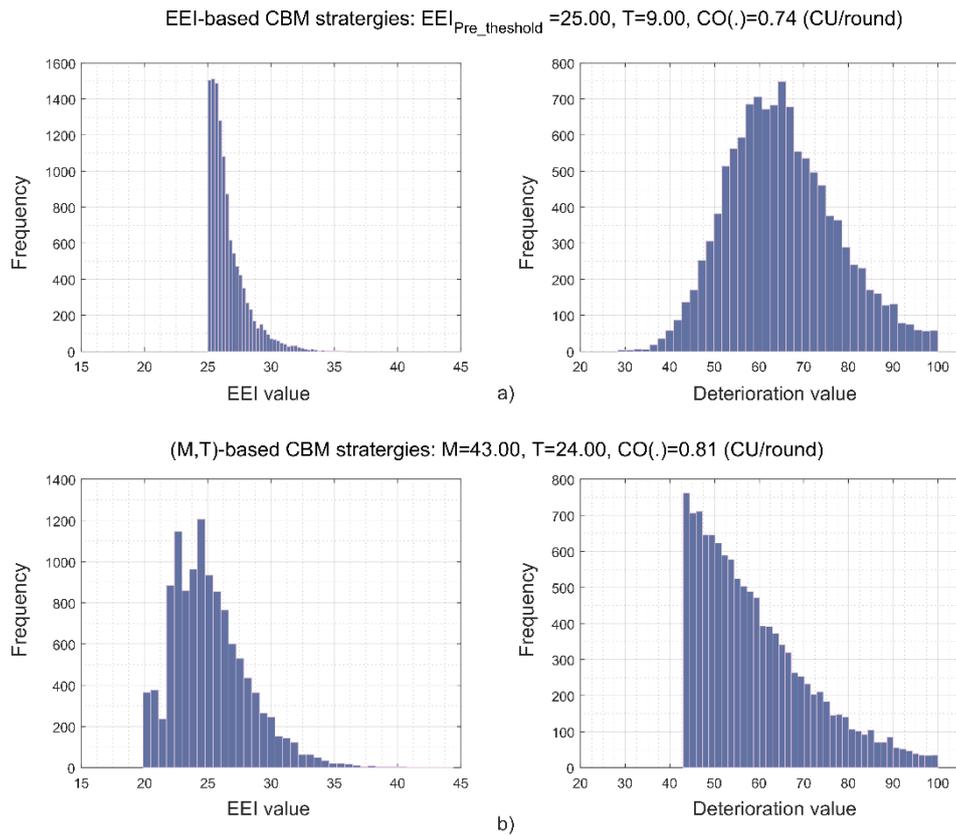


Figure 35. Distribution of condition indicators at preventive maintenance time which is based on a) EEI level and b) conventional deterioration level

It should be noticed that the performance of EEI-based CBM may depends on the value of other parameters.

6.4.2. Sensitivity analyses

From the previous results, the following sensitivity analyses are investigated for both EEI-based CBM and (M,T) policy:

- Sensitivity analysis to the inspection cost
- Sensitivity analysis to the preventive maintenance cost
- Sensitivity analysis to the energy cost rate
- Sensitivity analysis to the bearing deterioration behavior

6.4.2.1. Sensitivity analysis to inspection cost

In this study, the inspection cost (C_{in}^E for EEI-based maintenance and C_{in}^D for (M,T) policy) varies from 1 to 120. The obtained results in Table 8 show that the proposed EEI-based CBM provides a lower total cost than the (M,T) policy.

Table 8. Optimal results of two CBM policies: EE-based CBM and (M,T) CBM maintenance

EE-based CBM maintenance				(M,T) CBM maintenance			
C_{in}^E (CU)	$CO^*(.)$ (CU/round)	$EEI^*_{Pre_threshold}$ (Wh/round)	ΔT^* (month)	C_{in}^D (CU)	$CO^*(.)$ (CU/round)	M^*	ΔT^* (month)
1	0,741	25	9	1	0,794	47	22
10	0,787	22	57	10	0,813	43	24
20	0,792	23	63	20	0,836	25	82
30	0,816	20	61	30	0,856	30	84
40	0,832	13	65	40	0,875	29	86
50	0,846	15	75	50	0,895	30	88
60	0,866	12	73	60	0,916	31	90
70	0,881	21	75	70	0,935	36	92
80	0,901	11	79	80	0,954	36	94
90	0,916	15	73	90	0,973	39	96
100	0,928	15	83	100	0,989	39	98
110	0,946	14	77	110	1,015	41	100
120	0,958	7	79	120	1,030	43	102

6.4.2.2. Sensitivity analysis to preventive maintenance cost

The preventive maintenance cost C_p varies from 10 to 140 with step equals 10, the other parameters remain unchanged. The minimum cost rate given by both CBM policies is shown in Figure 36.

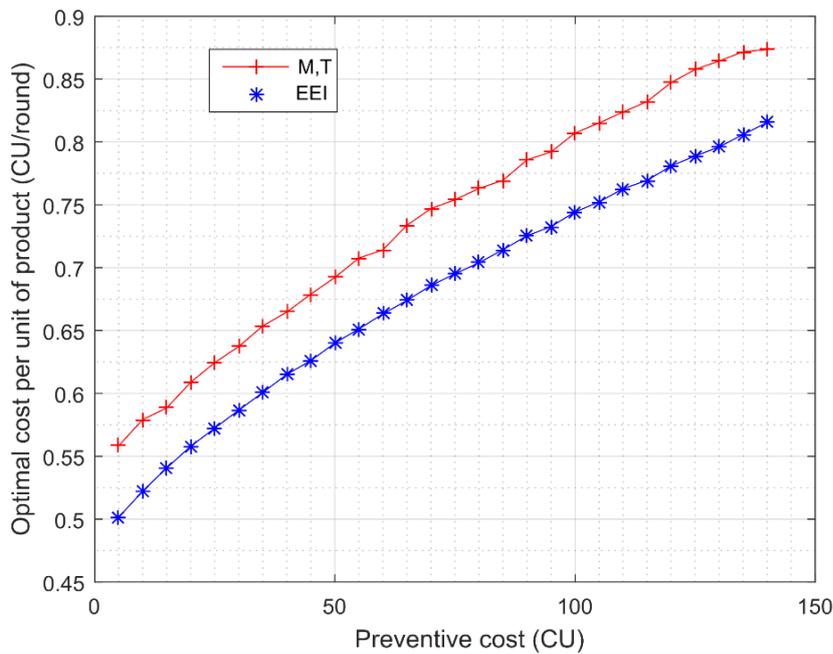


Figure 36. Total cost per product unit is a function of the preventive maintenance cost

6.4.2.3. Sensitivity analysis to energy cost rate

In the same manner, to investigate the impact of the energy cost rate E_p , the optimal maintenance policies provided by EEI-based CBM and (M,T) model are determined each value of E_p . In fact, energy cost rate E_p varies from 0.005 (CU/Wh) to 0.03 (CU/Wh) and the other parameters remain unchanged as shown in Table 7.

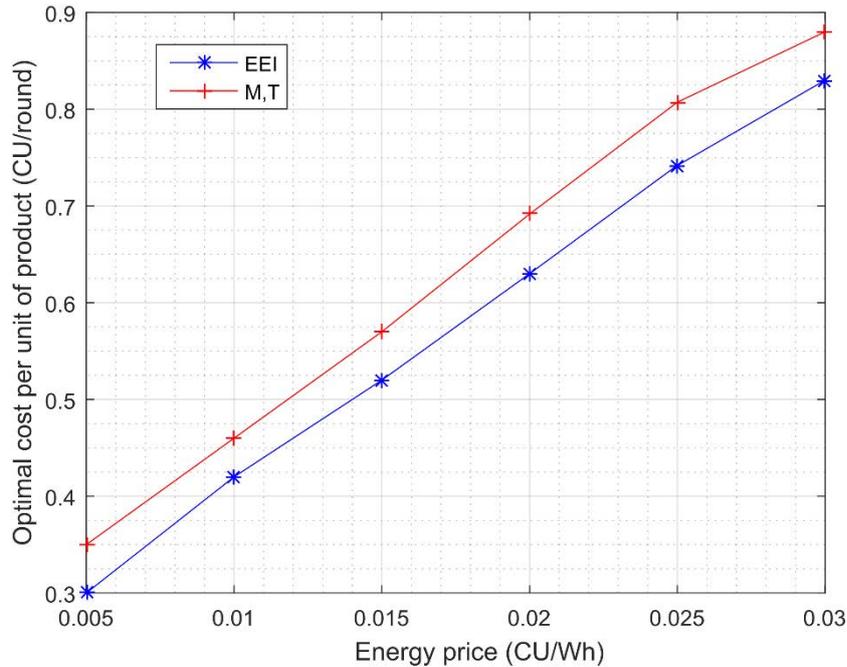


Figure 37. Total cost per product unit is a function of energy price

It shows again that the EEI-based CBM policy always provides a lower cost.

6.4.2.4. Sensitivity analysis to deterioration behaviors

Table 9 shows the total cost per product unit of two maintenance policies for different value of deterioration parameter β . The EEI-based CBM provides again a better result regarding to (M,T) policy. A cost saving is about 3% when $C_i^D = C_i^E = 10(CU)$. This amount shows that cost of saving is higher (9%) when $C_i^D = 10(CU)$; $C_i^E = 1(CU)$.

Table 9. Minimum total cost rate cost with different deterioration behaviours

β	$CO^*(.)$ (CU/round)		
	EEI-based CBM		(M,T) based CBM
	$C_i^E = 1$ (CU)	$C_i^E = 10$ (CU)	$C_i^D = 10$ (CU)
1,00	0,621	0,623	0,625
0,80	0,624	0,631	0,635
0,50	0,631	0,642	0,647
0,25	0,655	0,661	0,665
0,20	0,668	0,694	0,704
0,10	0,741	0,787	0,813

The results show the larger variation of the deterioration process (small value of β) the more cost saving provided by the proposed EEI-based CBM is.

6.5. Conclusion

In this chapter, a novel CBM maintenance is introduced by considering EEI as the decisional indicator for preventive maintenance-decision making. This EEI-based CBM tackles the issue related to integrate EE in CBM strategies (scientific issue n°4 in chapter 2). Two kinds of preventive maintenance rules are proposed to optimally select appropriate components to be preventively replaced. The first one, namely individual maintenance for which each component is individually selected according to its EEI level, leads to a large number of decision parameters ((N+1) decision parameters for a function/system composed of N components). For the second preventive maintenance policy, called grouping maintenance, a group of several components are jointly selected when the EEI of the whole function/system is lower than a prefixed EEI threshold. Thanks to the EEI consideration, only two decision parameters are needed whatever the number of components supporting the function/system.

To highlight the performance of the proposed EEI-based CBM maintenance, a classical CBM maintenance in which the preventive decision on each component is based on its physical deterioration level is also extended by integrating the energy cost into the existing cost model. It is important to note that the extended CBM maintenance, called (M,T) maintenance policy, lead to a large number of decision parameters to be optimized (each component requires one decision parameter).

Both the proposed EEI-based CBM and the (M,T) policy are applied for one motor of the platform TELMA. The various numerical studies show that the proposed EEI-based policy provides a better result (lower cost per product unit).

General conclusion

This core idea defended in this thesis is related to the necessary evolution of maintenance and more precisely CBM strategies for integrating Energy Efficiency (EE) in terms of EE Indicator (EEI) and REEL concepts, in the decision making phase.

These two EE concepts are representative of sustainability requirements which are required to be achieved now by the industrial system to face not only with economic, but also societal and environmental challenges (three pillars). In that way, the thesis addressed several issues which are related to the foundation of these concepts, their formulation, their evolutions in terms of value trends by considering dynamics of the system, their consideration in CBM, their first step of validation on a specific case ...

From these issues, it is promoted several contributions:

- The first ones developed in Chapter 3 are related to the generic definition of EEI for different abstraction levels and materialized by its two properties: energy consumption and physical useful output. Then a generic EEI formulation, usable at each level, is proposed. This formulation is described as the ratio between these two properties in which time-dependent factors (called static and dynamic factors) are considered. Formulation can serve latter for a specific manufacturing system to calculate EEI value and also EEI evolution (due to the time-dependent factors). Based on this EEI evolution, a novel concept named REEL (Remaining Energy-Efficient Lifetime) is introduced as the foundation of EEP (to assess the remaining time before a component/function/system lost its energy properties under a limit threshold),
- The second ones developed in Chapter 4 are related to a generic approach for implementing different steps required to use the generic formulation for EEI calculation on a specific manufacturing system and then to assess REEL. This generic approach is structured on three steps (Figure 14): (1) identification, at each abstraction level of the selected system, of the two EEI properties (energy consumption, useful manufactured product) but also of the impact factors. It leads to isolate or create models integrating these factors and supporting the properties modelling to obtain EEI models (specific formulations). (2) Implementation of prognostic method the most appropriated for

predicting the evolution of each impact factor. (3) Re-integration in the EEI model of the impact factors evolutions, to be able to track EEI evolution allowing to assess the REEL.

- The last ones developed in Chapter 6 are addressed, first, the proposal of a new EEI-based CBM model by using EEI value as a condition to trigger the preventive maintenance action. By considering EEI value of individual component and/or EEI value of system (as supported by EEI formalizations in chapter 3), two main preventive maintenance policies (individual maintenance and grouping maintenance) are proposed. Then, the cost-model of one existing CBM (named (M,T) maintenance policy) is extended by taking into account the energy cost (for considering energy in maintenance optimization). These two contributions aim at showing the interest of a new EEI-based CBM practice in terms of cost optimization with regards to conventional CBM strategies.

According to these contributions, the main originalities claimed are the consideration of EE as a key lever in industrial systems to face with sustainability issues, the foundation of EEI, the proposal of the new REEL concept to consider EEI evolution in decision making (EEP), the investigation of a new EE(I)-based CBM strategy for which the condition to be mastered is sustainability oriented.

Most of these contributions are generic and thus can be issued for different types of manufacturing systems and at each abstraction level of these systems.

In terms of validation, all the contributions have been applied on TELMA platform. In that way, the generic approach has been deployed to develop EEI models for the two electrical motors and also for the “punching” function achieved by these two motors. These EEI models are integrating the evolution of bearing deterioration, and of mission profile. The results obtained from these models have demonstrated that both EEI can be calculated at any time and the EE evolution (REEL values) can be predicted both at the component level and at the function level in the frame of a specific system.

Then it was used, at the motor level, the results of EEI calculation for implementing EEI-based CBM. In that way, Monte Carlo simulation technique was applied for finding the time of the first component replacement. This time was used in the extended model to calculate cost leading to select the optimal parameters (inspection interval and EEI threshold) minimizing this cost. In parallel, a conventional CBM strategy was applied by considering bearing deterioration level as condition. Then, the same tools (e.g. Monte Carlo, extended model) were used to decide

the optimal parameters. The comparison of the 2 minimized costs shown that EEI-based CBM appeared as an efficient policy when the quantity of energy consumption is high. It is always true when sensibility analysis are done by modifying: inspection cost, preventive maintenance cost, energy prices and deterioration behavior of one dynamic impact factor (bearing condition).

However, the contributions delivered during this thesis do not covered all the answers expected with regards to the two challenges. Indeed, the following aspects are not solved:

- The formalization expressed in challenge 1 is not fully satisfied by the EEI formulation. Moreover, the relationships between EEI and the other KPIs (conventional or not) have not been studied.
- EE-based CBM expressed in challenge is only approached with EEI without considering EEP.

Thus, some perspectives can be underlined for this thesis in face with the previous reports and also with regards to needs emerging from the work done. The main perspectives are:

- The extension of the validation context to prove the feasibility and the real benefits of the contributions (EE-based CBM) in a real industrial system (e.g. one possibility is to apply them on a press at the RENAULT factory located at Flins).
- The development of a “generic EE model” usable for the class of manufacturing system. This general model has to be a concretization of the textual formulation proposed in chapter 3 (e.g. knowledge formalization on energy resource – inputs, outputs, the impact factors, the relationships and rules between them, the prognostics on impact factors etc.). It should allow to define particular EE-model for a specific component, a specific function or a specific level by implementing an instantiation procedure of the generic EE-model.
- The implementation of the REEL(EEP)-based CBM which has to be considered as an extension of the current EEI-based CBM.
- Consideration of others sustainability KPIs than EE but also of conventional KPIs and of all the relationships between these different KPIs in the maintenance decision-making process.
- Development of multi-criteria approach for optimizing maintenance decision-making process from the consideration both of conventional (e.g. RUL) and sustainability KPIs

(EE but not only; e.g. REEL, EEI, CO²) interacting together in terms of positive or negative impacts.

Publications of the Author

Journal papers:

- [193] A. Hoang, P. Do, and B. Iung, “Energy efficiency performance-based prognostics for aided maintenance decision-making: Application to a manufacturing platform,” *Journal of Cleaner Production*, vol. 142, pp. 1–20, 2016.
- [194] A. Hoang, P. Do Van, B. Iung, E. Levrat, and A. Voisin, “Considération d’un indicateur d’efficacité énergétique pour la prise de décision en maintenance : de sa définition au fondement de son pronostic,” *Journal Européen des Systèmes Automatisés (JESA)*, vol. 49, no. 4–5, pp. 559–578, 2016.

Conference papers:

- [174] A. Hoang, P. Do, B. Iung, E. Levrat, and A. Voisin, “Performance d’efficacité énergétique: concepts et pronostic,” in *10 ème Conférence Francophone de Modélisation, Optimisation et Simulation- MOSIM’14*, 2014, p. 107.
- [191] A. Hoang, P. Do, B. Iung, E. Levrat, and A. Voisin, “Prognostics and Energy Efficiency : Survey and Investigations,” in *European Conference of the Prognostics and Health Management Society 2014*, 2014, pp. 147–161.
- [198] A. Hoang, P. Do, and B. Iung, “Prognostics on Energy Efficiency Performance for Maintenance Decision-Making: Application to Industrial Platform TELMA,” in *2015 Prognostics and System Health Management Conference-Beijing (2015 PHM-Beijing)*, 2015.
- [204] A. Hoang, P. Do, and B. Iung, “Integrating Energy Efficiency-Based Prognostic Approaches into Energy Management Systems of Base Stations,” in *The 2014 International Conference on Advanced Technologies for Communications (ATC’14)*, 2014, pp. 220–225.
- [211] A. Hoang, P. Do, and B. Iung, “Investigation on the use of energy efficiency for condition-based maintenance,” in *The 3rd IFAC AMEST workshop*, 2016.

Bibliography

- [1] European Commission, “Energy challenges and policy,” *European Commission*, 2013.
- [2] G. Liu, “Development of a general sustainability indicator for renewable energy systems: A review,” *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 611–621, Mar. 2014.
- [3] V. V. Prabhu, D. Trentesaux, and M. Taisch, “Energy-aware manufacturing operations,” *International Journal of Production Research*, vol. 53, no. 23, pp. 6994–7004, 2015.
- [4] K. E. K. Vimala, S. Vinodha, and R. Muralidharan, “An approach for evaluation of process sustainability using multi-grade fuzzy method,” *International Journal of Sustainable Engineering*, vol. 8, no. April, pp. 40–54, 2015.
- [5] A. V. H. Sola, C. M. D. M. Mota, and J. L. Kovaleski, “A model for improving energy efficiency in industrial motor system using multicriteria analysis,” *Energy Policy*, vol. 39, no. 6, pp. 3645–3654, Jun. 2011.
- [6] J. R. Dufrou *et al.*, “Towards energy and resource efficient manufacturing: A processes and systems approach,” *CIRP Annals - Manufacturing Technology*, vol. 61, no. 2, pp. 587–609, Jan. 2012.
- [7] M. Mora, J. Vera, C. Rocamora, and R. Abadia, “Energy Efficiency and Maintenance Costs of Pumping Systems for Groundwater Extraction,” *Water Resources Management*, vol. 27, no. 12, pp. 4395–4408, 2013.
- [8] C. S. Byington, M. J. Roemer, and T. Galie, “Prognostic enhancements to diagnostic systems for improved condition-based maintenance [military aircraft],” in *Proceedings, IEEE Aerospace Conference*, 2002, vol. 6, pp. 6-2815-6–2824.
- [9] S. Sankararaman, M. Daigle, A. Saxena, and K. Goebel, “Analytical algorithms to quantify the uncertainty in remaining useful life prediction,” *2013 IEEE Aerospace Conference*, pp. 1–11, Mar. 2013.
- [10] B. Saha, K. Goebel, S. Poll, and J. Christophersen, “A Bayesian Framework for Remaining Useful Life Estimation,” *Proceedings of AAAI Fall Symposium: AI for Prognostics (Working Notes)*, pp. 1–6, 2007.
- [11] A. Saxena, J. Celaya, B. Saha, S. Saha, and K. Goebel, “Metrics for Offline Evaluation of Prognostic Performance,” *International Journal of Prognostics and Health Management*, pp. 1–20, 2010.
- [12] N. S. Clements, “Introduction to Prognostics,” *Presented at Annual Conference of the*

PHM Society Montreal, Canada, 2011.

- [13] X. Lei, P. Sandborn, R. Bakhshi, A. Kashani-pour, and N. Goudarzi, "PHM Based Predictive Maintenance Optimization for Offshore Wind Farms," in *Prognostics and Health Management (PHM), 2015 IEEE*, 2015, pp. 1–8.
- [14] B. Zhang, L. Zhang, and J. Xu, "Degradation Feature Selection for Remaining Useful Life Prediction of Rolling Element Bearings," *Quality and Reliability Engineering International*, p. n/a-n/a, 2015.
- [15] B. Liu, Z. Xu, M. Xie, and W. Kuo, "A value-based preventive maintenance policy for multi-component system with continuously degrading components," *Reliability Engineering & System Safety*, vol. 132, pp. 83–89, Dec. 2014.
- [16] W. Xu and L. Cao, "Energy efficiency analysis of machine tools with periodic maintenance," *International Journal of Production Research*, no. March, pp. 1–13, Mar. 2014.
- [17] B. Darabnia and M. Demichela, "Maintenance an opportunity for energy saving," *Chemical Engineering Transactions*, vol. 33, pp. 259–264, 2013.
- [18] R. M. C. Ratnayake, "Sustainable performance of industrial assets: the role of PAS 55-1&2 and human factors," *International Journal of Sustainable Engineering*, vol. 6, no. 3, pp. 198–211, 2013.
- [19] S. N. Morioka and M. M. de Carvalho, "A Systematic Literature Review Towards a Conceptual Framework for Integrating Sustainability Performance into Business," *Journal of Cleaner Production*, vol. 136, pp. 1–28, 2016.
- [20] R. A. R. Ghazilla, N. Sakundarini, S. H. Abdul-Rashid, N. S. Ayub, E. U. Olugu, and S. N. Musa, "Drivers and barriers analysis for green manufacturing practices in Malaysian smes: A preliminary findings," *Procedia CIRP*, vol. 26, pp. 658–663, 2015.
- [21] A. M. Deif, "A system model for green manufacturing," *Journal of Cleaner Production*, vol. 19, no. 14, pp. 1553–1559, 2011.
- [22] A. Fysikopoulos, D. Anagnostakis, K. Salonitis, and G. Chryssolouris, "An Empirical Study of the Energy Consumption in Automotive Assembly," *45th CIRP Conference on Manufacturing Systems 2012*, vol. Procedia C, pp. 477–482, Jan. 2012.
- [23] S. Thiede, G. Bogdanski, and C. Herrmann, "A Systematic Method for Increasing the Energy and Resource Efficiency in Manufacturing Companies," *Procedia CIRP*, vol. 2, pp. 28–33, Jan. 2012.
- [24] S. Wang, X. Lu, X. X. Li, and W. D. Li, "A systematic approach of process planning and

- scheduling optimization for sustainable machining,” *Journal of Cleaner Production*, vol. 87, no. C, pp. 914–929, 2015.
- [25] T. Spiering, S. Kohlitz, H. Sundmaeker, and C. Herrmann, “Energy efficiency benchmarking for injection moulding processes,” *Robotics and Computer-Integrated Manufacturing*, vol. 36, pp. 45–59, 2015.
- [26] K. A. H. Kobbacy and D. N. P. Murthy, *Complex System Maintenance Handbook*. 2008.
- [27] H. G. Mobtaker, A. Akram, A. Keyhani, and A. Mohammadi, “Optimization of energy required for alfalfa production using data envelopment analysis approach,” *Energy for Sustainable Development*, vol. 16, no. 2, pp. 242–248, 2012.
- [28] World Commission on Environment and Development, “Our Common Future: Report of the World Commission on Environment and Development,” 1987.
- [29] S. Schaltegger and M. Wagner, “Integrative management of sustainability performance, measurement and reporting,” *International Journal of Accounting, Auditing and Performance Evaluation*, vol. 3, no. 1, p. 1, 2006.
- [30] A. Sabapathy, S. K. V. Ragavan, M. Vijendra, and A. G. Nataraja, “Energy efficiency benchmarks and the performance of LEED rated buildings for Information Technology facilities in Bangalore, India,” *Energy and Buildings*, vol. 42, no. 11, pp. 2206–2212, Nov. 2010.
- [31] W.-R. Bretzke and K. Barkawi, *Sustainable Logistics: Responses to a Global Challenge*. 2012.
- [32] J. Elkington, *Cannibals with forks : the triple bottom line of 21st century business*. New Society Publishers, 1998.
- [33] Joseph Fiksel, T. Eason, and H. Frederickson, “A Framework for Sustainability Indicators at EPA,” 2012.
- [34] T. Peng, X. Xu, and L. Wang, “A novel energy demand modelling approach for CNC machining based on function blocks,” *Journal of Manufacturing Systems*, vol. 33, no. 1, pp. 196–208, 2014.
- [35] J. D. Hearn et al., “The sustainability of new technologies in vehicular transportation,” *2011 IEEE Vehicle Power and Propulsion Conference, VPPC 2011*, 2011.
- [36] R. M. Chandima Ratnayake and T. Markeset, “Asset integrity management for sustainable industrial operations: measuring the performance,” *International Journal of Sustainable Engineering*, vol. 5, no. 2, pp. 145–158, 2012.
- [37] K. Salonitis and P. Ball, “Energy Efficient Manufacturing from Machine Tools to

- Manufacturing Systems,” *Procedia CIRP*, vol. 7, pp. 634–639, Jan. 2013.
- [38] International Energy Agency, “Energy Efficiency Indicators - Highlights,” 2016.
- [39] D. M. Özşahin, B. Sezen, and S. Y. Çankaya, “Effects of Green Manufacturing and Eco-innovation on Sustainability Performance,” *Procedia - Social and Behavioral Sciences*, vol. 99, pp. 154–163, 2013.
- [40] S. Thiede, *Sustainable Production , Life Cycle Engineering and Management*. 2012.
- [41] D. Küpper, K. Kuhlmann, S. Köcher, T. Dauner, and P. Burggräf, “The factory of the future,” 2016.
- [42] E. Sari, A. M. Shaharoun, A. Ma’aram, and a. M. Yazid, “Sustainable Maintenance Performance Measures: A Pilot Survey in Malaysian Automotive Companies,” *Procedia CIRP*, vol. 26, pp. 443–448, 2015.
- [43] C. D. F. Gonçalves, J. A. M. Dias, and V. A. C. Machado, “Multi-criteria decision methodology for selecting maintenance key performance indicators,” *International Journal of Management Science and Engineering Management*, vol. 9653, no. January 2015, pp. 1–9, 2014.
- [44] F. Shrouf, G. Bing, and J. Ordieres-Meré, “Multi-level awareness of energy used in production processes,” *Journal of Cleaner Production*, pp. 1–16, 2016.
- [45] S. O. Duffuaa and M. Ben-Daya, *Handbook of Maintenance Management and Engineering*. 2009.
- [46] A. Azapagic and S. Perdan, “Indicators of sustainable development for industry: a general framework,” *Trans IChemE*, vol. 78, no. July, pp. 243–261, 2000.
- [47] ISO, “ISO 50001:2011 Energy management systems - Requirements with guidance for use,” *International Organization for Standardization.*, 2011. [Online]. Available: <https://www.iso.org/obp/ui/#iso:std:iso:50001:ed-1:v1:en>. [Accessed: 23-Apr-2014].
- [48] European Commission, “Reference document on best available techniques for energy efficiency,” 2009.
- [49] B. Iung and A. C. Marquez, “Special issue on e-maintenance,” *Computers in Industry*, vol. 57, no. 6, pp. 473–475, 2006.
- [50] International Energy Agency, “Capturing the Multiple Benefits of Energy Efficiency: Executive Summary,” *Capturing the Multiple Benefits of Energy Efficiency*, pp. 18–25, 2014.
- [51] G. a. Boyd, “Estimating the changes in the distribution of energy efficiency in the U.S. automobile assembly industry,” *Energy Economics*, vol. 42, pp. 81–87, Mar. 2014.

- [52] L. Peng, X. Zeng, Y. Wang, and G.-B. Hong, "Analysis of energy efficiency and carbon dioxide reduction in the Chinese pulp and paper industry," *Energy Policy*, vol. 80, pp. 65–75, 2015.
- [53] E. Worrell, R. F. a. Cuelenaere, K. Blok, and W. C. Turkenburg, "Energy consumption by industrial processes in the European Union," *Energy*, vol. 19, no. 11, pp. 1113–1129, 1994.
- [54] A. Motevali, S. Minaei, M. H. Khoshtaghaza, and H. Amirnejat, "Comparison of energy consumption and specific energy requirements of different methods for drying mushroom slices," *Energy*, vol. 36, no. 11, pp. 6433–6441, 2011.
- [55] T. Virtanen, M. Tuomaala, and E. Pentti, "Energy efficiency complexities: A technical and managerial investigation," *Management Accounting Research*, vol. 24, no. 4, pp. 401–416, Dec. 2013.
- [56] A. Svensson and S. Paramonova, "An analytical model for identifying and addressing energy efficiency improvement opportunities in industrial production systems – model development and testing experiences from Sweden," *Journal of Cleaner Production*, no. June 2014, 2016.
- [57] F. Apostolos, P. Alexios, P. Georgios, S. Panagiotis, and C. George, "Energy Efficiency of Manufacturing Processes: A Critical Review," *Procedia CIRP*, vol. 7, pp. 628–633, Jan. 2013.
- [58] A. Atmaca and R. Yumrutaş, "Analysis of the parameters affecting energy consumption of a rotary kiln in cement industry," *Applied Thermal Engineering*, vol. 66, no. 1–2, pp. 435–444, 2014.
- [59] L. Ryan and N. Campbell, "Spreading the net : the multiple benefits of energy efficiency improvements," 2012.
- [60] A. Trianni and E. Cagno, "Dealing with barriers to energy efficiency and SMEs: Some empirical evidences," *Energy*, vol. 37, no. 1, pp. 494–504, Jan. 2012.
- [61] The Energy Efficiency Financial Institutions Group, "Energy Efficiency – the first fuel for the EU Economy," 2015.
- [62] K. Bunse, M. Vodicka, P. Schönsleben, M. Brühlhart, and F. O. Ernst, "Integrating energy efficiency performance in production management – gap analysis between industrial needs and scientific literature," *Journal of Cleaner Production*, vol. 19, no. 6–7, pp. 667–679, Apr. 2011.
- [63] B. Zou, M. Elke, M. Hansen, and N. Kafle, "Evaluating air carrier fuel efficiency in the

- US airline industry,” *Transportation Research Part A: Policy and Practice*, vol. 59, pp. 306–330, Jan. 2014.
- [64] T. Fleiter, D. Fehrenbach, E. Worrell, and W. Eichhammer, “Energy efficiency in the German pulp and paper industry – A model-based assessment of saving potentials,” *Energy*, vol. 40, no. 1, pp. 84–99, Apr. 2012.
- [65] M. Moghavvemi, M. S. Ismail, B. Murali, S. S. Yang, a. Attaran, and S. Moghavvemi, “Development and optimization of a PV/diesel hybrid supply system for remote controlled commercial large scale FM transmitters,” *Energy Conversion and Management*, vol. 75, pp. 542–551, Nov. 2013.
- [66] B. Mangu, K. Kiran Kumar, and B. G. Fernandes, “Efficiency improvement of solar-wind based dual-input converter for telecom power supply,” *2012 11th International Conference on Environment and Electrical Engineering*, pp. 914–919, May 2012.
- [67] S. Mekhilef, R. Saidur, and M. Kamalisarvestani, “Effect of dust, humidity and air velocity on efficiency of photovoltaic cells,” *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, pp. 2920–2925, Jun. 2012.
- [68] K. Tanaka, “Assessing measures of energy efficiency performance and their application in industry,” 2008.
- [69] S. Gavankar and R. Geyer, “The rebound effect: State of the Debate and Implications for Energy Efficiency Research,” 2011.
- [70] D. Hsu, “How much information disclosure of building energy performance is necessary?,” *Energy Policy*, vol. 64, pp. 263–272, Jan. 2014.
- [71] F. Ruzzenenti and R. Basosi, “Evaluation of the energy efficiency evolution in the European road freight transport sector,” *Energy Policy*, vol. 37, no. 10, pp. 4079–4085, Oct. 2009.
- [72] Lloyd’s Register, “Implementing the Energy Efficiency Design Index (EEDI) Guidance for owners , operators and shipyards,” 2012.
- [73] D. Phylipsen, K. Blok, E. Worrell, and J. De Beer, “Benchmarking the energy efficiency of Dutch industry: an assessment of the expected effect on energy consumption and CO2 emissions,” *Energy Policy*, vol. 30, no. 8, pp. 663–679, Jun. 2002.
- [74] L. Xu and J. Yang, “Introduction to Multi-Criteria Decision Making and the Evidential Reasoning Approach,” no. 106, pp. 1–21, 2001.
- [75] Grayson C. Heffner, P. du Pont, G. Rybka, C. Paton, L. Roy, and D. Limaye, “Energy Provider-Delivered Energy Efficiency,” *The International Energy Agency*. p. 145, 2013.

- [76] C. Schmidt, W. Li, S. Thiede, S. Kara, and C. Herrmann, "A methodology for customized prediction of energy consumption in manufacturing industries," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 2, no. 2, pp. 163–172, 2015.
- [77] M. Deruyck *et al.*, "Power consumption in wireless access network," in *2010 European Wireless Conference (EW)*, 2010, pp. 924–931.
- [78] M. Schulze, H. Nehler, M. Ottosson, and P. Thollander, "Energy management in industry - A systematic review of previous findings and an integrative conceptual framework," *Journal of Cleaner Production*, vol. 112, pp. 3692–3708, 2016.
- [79] E. K. Yamakawa, A. R. Aoki, L. C. Siebert, G. Klinguelfus, and P. A. Cauchick Miguel, "A Fuzzy-QFD decision making approach for selecting industry energy efficiency indicators," *2013 IEEE PES Conference on Innovative Smart Grid Technologies, ISGT LA 2013*, pp. 0–4, 2013.
- [80] T.-Y. Chiu, S.-L. Lo, and Y.-Y. Tsai, "Establishing an Integration-Energy-Practice Model for Improving Energy Performance Indicators in ISO 50001 Energy Management Systems," *Energies*, vol. 5, no. 12, pp. 5324–5339, Dec. 2012.
- [81] S. Wiel, C. Egan, and M. delta Cava, "Energy efficiency standards and labels provide a solid foundation for economic growth, climate change mitigation, and regional trade," *Energy for Sustainable Development*, vol. 10, no. 3, pp. 54–63, Sep. 2006.
- [82] McKane and Aimee, "Thinking Globally: How ISO 50001 - Energy Management can make industrial energy efficiency standard practice," *Lawrence Berkeley National Laboratory*, Jul. 2010.
- [83] A. Trianni, E. Cagno, and A. De Donatis, "A framework to characterize energy efficiency measures," *Applied Energy*, vol. 118, pp. 207–220, Apr. 2014.
- [84] A. Kostevšek, J. Petek, L. Čuček, and A. Pivec, "Conceptual design of a municipal energy and environmental system as an efficient basis for advanced energy planning," *Energy*, vol. 60, pp. 148–158, Oct. 2013.
- [85] A. Dietmair and A. Verl, "A generic energy consumption model for decision making and energy efficiency optimisation in manufacturing," *International Journal of Sustainable Engineering*, 2009.
- [86] O. Ekren, M. A. Ezan, and A. Erek, "Experimental assessment of energy storage via variable speed compressor," *International Journal of Refrigeration*, vol. 34, no. 6, pp. 1424–1435, 2011.

- [87] B. Darabnia and M. Demichela, “Data Field for Decision Making in Maintenance Optimization: An Opportunity for Energy Saving,” *Chemical engineering transactions*, vol. 33, pp. 259–264, 2013.
- [88] P. Zhou and B. W. Ang, “Linear programming models for measuring economy-wide energy efficiency performance,” *Energy Policy*, vol. 36, no. 8, pp. 2911–2916, Aug. 2008.
- [89] O. Hasan and a. F. M. Arif, “Performance and life prediction model for photovoltaic modules: Effect of encapsulant constitutive behavior,” *Solar Energy Materials and Solar Cells*, vol. 122, pp. 75–87, Mar. 2014.
- [90] European Committee for Standardization, “NF EN 13306 -Maintenance terminology,” 2007.
- [91] Juan Sebastian Borrero Raha Akhavan-Tabatabaei, “A Markov Decision Process model for optimal policy making in the maintenance of a single-machine single-product toolset,” in *the 2010 Winter Simulation Conference*, 2010, pp. 2594–2605.
- [92] E. Alay, K. Duran, and A. Korlu, “A sample work on green manufacturing in textile industry,” *Sustainable Chemistry and Pharmacy*, vol. 3, pp. 39–46, 2016.
- [93] J. Endrenyi and G. J. Anders, “Aging, maintenance, and reliability - approaches to preserving equipment health and extending equipment life,” *IEEE Power and Energy Magazine*, vol. 4, no. june, pp. 59–67, 2006.
- [94] J. C. Banks, M. Lebold, K. M. Reichard, J. A. Hines, and M. S. Brought, “Platform degrader analysis for the complex systems for the design and application of condition based maintenance,” in *2014 IEEE Aerospace Conference*, 2014, pp. 1–12.
- [95] J.-H. Shin and H.-B. Jun, “On condition based maintenance policy,” *Journal of Computational Design and Engineering*, vol. 2, no. 2, pp. 119–127, 2015.
- [96] M. Jouin, R. Gouriveau, D. Hissel, M.-C. Péra, and N. Zerhouni, “Prognostics and Health Management of PEMFC – State of the art and remaining challenges,” *International Journal of Hydrogen Energy*, vol. 38, no. 35, pp. 15307–15317, Nov. 2013.
- [97] T. Welte, *Thomas Welte Deterioration and Maintenance Models for Components in Hydropower Plants*, no. May. 2008.
- [98] A. C. Márquez, *The Maintenance Management Framework: Models and Methods for Complex Systems Maintenance*. 2007.
- [99] M. Bengtsson, “Condition Based Maintenance Systems: An Investigation of Technical Constituents and Organizational Aspects,” 2004.

- [100] B. de Jonge, R. Teunter, and T. Tinga, "The influence of practical factors on the benefits of condition-based maintenance over time-based maintenance," *Reliability Engineering and System Safety*, vol. 158, no. October 2016, pp. 21–30, 2017.
- [101] R. Ahmad and S. Kamaruddin, "An overview of time-based and condition-based maintenance in industrial application," *Computers & Industrial Engineering*, vol. 63, no. 1, pp. 135–149, Aug. 2012.
- [102] D. Galar, A. Thaduri, M. Catelani, and L. Ciani, "Context awareness for maintenance decision making: A diagnosis and prognosis approach," *Measurement: Journal of the International Measurement Confederation*, vol. 67, pp. 137–150, 2015.
- [103] B. Balta, F. O. Sonmez, and A. Cengiz, "Speed losses in V-ribbed belt drives," *Mechanism and Machine Theory*, vol. 86, pp. 1–14, 2015.
- [104] H. Shao, H. L. Wang, and X. M. Zhao, "A cutting power model for tool wear monitoring in milling," *International Journal of Machine Tools and Manufacture*, vol. 44, no. 14, pp. 1503–1509, 2004.
- [105] A. Coraddu, L. Oneto, A. Ghio, S. Savio, M. Figari, and D. Anguita, "Machine learning for wear forecasting of naval assets for condition-based maintenance applications," *Electrical Systems for Aircraft, Railway and Ship Propulsion, ESARS*, vol. 2015–May, no. M1, 2015.
- [106] K. T. Huynh, A. Grall, and C. Bérenguer, "Assessment of diagnostic and prognostic condition indices for efficient and robust maintenance decision-making of systems subject to stress corrosion cracking," *Reliability Engineering & System Safety*, vol. 159, no. November 2015, pp. 237–254, 2016.
- [107] J. Ben-Ali, B. Chebel-Morello, L. Saidi, S. Malinowski, and F. Fnaiech, "Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network," *Mechanical Systems and Signal Processing*, vol. 56–57, pp. 150–172, 2015.
- [108] Z. Tian and H. Liao, "Condition based maintenance optimization for multi-component systems using proportional hazards model," *Reliability Engineering & System Safety*, vol. 96, no. 5, pp. 581–589, May 2011.
- [109] H. Wang, D. Lin, J. Qiu, L. Ao, Z. Du, and B. He, "Research on multiobjective group decision-making in condition-based maintenance for transmission and transformation equipment based on D-S evidence theory," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 1035–1045, 2015.

- [110] M. Lebold, K. Reichard, and D. Boylan, "Utilizing dcom in an open system architecture framework for machinery monitoring and diagnostics," *IEEE Aerospace Conference Proceedings*, vol. 3, pp. 1227–1236, 2003.
- [111] M. Faccio, a. Persona, F. Sgarbossa, and G. Zanin, "Industrial maintenance policy development: A quantitative framework," *International Journal of Production Economics*, vol. 147, pp. 85–93, Jan. 2014.
- [112] H. Shi and J. Zeng, "Real-time prediction of remaining useful life and preventive opportunistic maintenance strategy for multi-component systems considering stochastic dependence," *Computers and Industrial Engineering*, vol. 93, pp. 192–204, 2016.
- [113] P. DO VAN *et al.*, "Remaining useful life (RUL) based maintenance decision making for deteriorating systems," *2nd IFAC Workshop on Advanced Maintenance Engineering, Service and Technology (A-Mest'12)*, vol. 45, no. 31, pp. 66–72, 2012.
- [114] D. Wang, F. Yang, K. Tsui, Q. Zhou, and S. J. Bae, "Remaining Useful Life Prediction of Lithium-Ion Batteries Based on Spherical Cubature Particle Filter," pp. 1–10, 2016.
- [115] X. Ye and X. Xia, *Optimal lighting project maintenance planning by a control system approach*, vol. 19, no. 3. IFAC, 2014.
- [116] M. B. Yildirim and F. G. Nezami, "Integrated maintenance and production planning with energy consumption and minimal repair," *The International Journal of Advanced Manufacturing Technology*, vol. 74, no. 9–12, pp. 1419–1430, 2014.
- [117] M. L. Neves, L. P. Santiago, and C. A. Maia, "A condition-based maintenance policy and input parameters estimation for deteriorating systems under periodic inspection," *Computers & Industrial Engineering*, vol. 61, no. 3, pp. 503–511, 2011.
- [118] A. Oyarbide-Zubillaga, A. Goti, and A. Sanchez, "Preventive maintenance optimisation of multi-equipment manufacturing systems by combining discrete event simulation and multi-objective evolutionary algorithms," *Production Planning & Control*, vol. 19, no. 4, pp. 342–355, Jun. 2008.
- [119] S. M. R. Iravani and I. Duenyas, "Integrated maintenance and production control of a deteriorating production system," *IIE Transactions (Institute of Industrial Engineers)*, vol. 34, no. 5, pp. 423–435, 2002.
- [120] D. P. Xenos, G. M. Kopanos, M. Ciccotti, and N. F. Thornhill, "Operational optimization of networks of compressors considering condition-based maintenance," *Computers & Chemical Engineering*, vol. 84, pp. 117–131, 2016.
- [121] M. G. Patterson, "What is energy efficiency? Concepts , indicators and methodological

- issues,” *Energy Polic*, vol. 24, no. 5, pp. 377–390, 1996.
- [122] A. Hilke and R. Lisa, “Mobilising investment in energy efficiency,” 2012.
- [123] I. W. H. Parry, D. Evans, and W. E. Oates, “Are energy efficiency standards justified?,” *Journal of Environmental Economics and Management*, pp. 1–22, Dec. 2013.
- [124] R. Centre, P. Cddex, and R. April, “Energy signature models for commercial buildings : test with measured data and interpretation,” *Energy and Buildings*, vol. 19, pp. 143–154, 1992.
- [125] S. Chirarattananon, P. Chaiwiwatworakul, V. D. Hien, P. Rakkwamsuk, and K. Kubaha, “Assessment of energy savings from the revised building energy code of Thailand,” *Energy*, vol. 35, no. 4, pp. 1741–1753, Apr. 2010.
- [126] B. W. Ang and X. Y. Xu, “Tracking industrial energy efficiency trends using index decomposition analysis,” *Energy Economics*, vol. 40, pp. 1014–1021, Nov. 2013.
- [127] W. Li, A. Zein, S. Kara, and C. Herrmann, “An Investigation into Fixed Energy Consumption of Machine Tools,” in *Glocalized Solutions for Sustainability in Manufacturing*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 268–273.
- [128] R. I. Rabady, “Optimized spectral splitting in thermo-photovoltaic system for maximum conversion efficiency,” *Energy*, pp. 1–8, 2016.
- [129] K. Tanaka, “Assessment of energy efficiency performance measures in industry and their application for policy,” *Energy Policy*, vol. 36, no. 8, pp. 2887–2902, Aug. 2008.
- [130] D. Y.-L. Chan, C.-F. Huang, W.-C. Lin, and G.-B. Hong, “Energy efficiency benchmarking of energy-intensive industries in Taiwan,” *Energy Conversion and Management*, vol. 77, pp. 216–220, Jan. 2014.
- [131] Y. J. Bor, “Consistent multi-level energy efficiency indicators and their policy implications,” *Energy Economics*, vol. 30, no. 5, pp. 2401–2419, Sep. 2008.
- [132] J. C. . Farla and K. Blok, “The use of physical indicators for the monitoring of energy intensity developments in the Netherlands, 1980–1995,” *Energy*, vol. 25, no. 7, pp. 609–638, Jul. 2000.
- [133] A. H. C. Dos Santos, M. T. W. Fagá, and E. M. Dos Santos, “The risks of an energy efficiency policy for buildings based solely on the consumption evaluation of final energy,” *International Journal of Electrical Power & Energy Systems*, vol. 44, no. 1, pp. 70–77, Jan. 2013.
- [134] F. Liu, J. Xie, and S. Liu, “A method for predicting the energy consumption of the main driving system of a machine tool in a machining process,” *Journal of Cleaner*

Production, pp. 1–7, Sep. 2014.

- [135] X. Fang, W. Chen, Z. Zhou, and Y. Xu, “Empirical models for efficiency and mass flow rate of centrifugal compressors,” *International Journal of Refrigeration*, vol. 41, pp. 190–199, 2014.
- [136] L. Yang, L. X. Zhao, C. L. Zhang, and B. Gu, “Loss-efficiency model of single and variable-speed compressors using neural networks,” *International Journal of Refrigeration*, vol. 32, no. 6, pp. 1423–1432, 2009.
- [137] J. Liu, Q. Li, F. Wang, and L. Zhou, “A new model of screw compressor for refrigeration system simulation,” *International Journal of Refrigeration*, vol. 35, no. 4, pp. 861–870, 2012.
- [138] S. Mousavi, S. Kara, and B. Kornfeld, “Energy efficiency of compressed air systems,” *Procedia CIRP*, vol. 15, pp. 313–318, 2014.
- [139] M. Benedetti, V. Cesarotti, and V. Introna, “From energy targets setting to energy-aware operations control and back: An advanced methodology for energy efficient manufacturing,” *Journal of Cleaner Production*, 2016.
- [140] M. R. N. Vilanova and J. A. P. Balestieri, “Modeling of hydraulic and energy efficiency indicators for water supply systems,” *Renewable and Sustainable Energy Reviews*, vol. 48, pp. 540–557, 2015.
- [141] C. Mose and N. Weinert, “Process chain evaluation for an overall optimization of energy efficiency in manufacturing—The welding case,” *Robotics and Computer-Integrated Manufacturing*, vol. 34, pp. 44–51, 2015.
- [142] R. Saidur, “A review on electrical motors energy use and energy savings,” *Renewable and Sustainable Energy Reviews*, vol. 14, no. 3, pp. 877–898, Apr. 2010.
- [143] E. El-Kharashi and M. El-Dessouki, “Coupling induction motors to improve the energy conversion process during balanced and unbalanced operation,” *Energy*, vol. 65, pp. 511–516, Feb. 2014.
- [144] R. Saidur, S. Mekhilef, M. B. Ali, a. Safari, and H. a. Mohammed, “Applications of variable speed drive (VSD) in electrical motors energy savings,” *Renewable and Sustainable Energy Reviews*, vol. 16, no. 1, pp. 543–550, Jan. 2012.
- [145] Y. He, B. Liu, X. Zhang, H. Gao, and X. Liu, “A modeling method of task-oriented energy consumption for machining manufacturing system,” *Journal of Cleaner Production*, vol. 23, no. 1, pp. 167–174, 2012.
- [146] T. Behrendt, A. Zein, and S. Min, “Development of an energy consumption monitoring

- procedure for machine tools,” *CIRP Annals - Manufacturing Technology*, vol. 61, no. 1, pp. 43–46, Jan. 2012.
- [147] C. J. Cahill and B. P. O Gallachoir, “Combining physical and economic output data to analyse energy and CO2 emissions trends in industry,” *Energy Policy*, vol. 49, pp. 422–429, Oct. 2012.
- [148] J. Sathaye and Publication, *Energy Efficiency Indicators Methodology Booklet*. 2010.
- [149] P. Dehning, S. Thiede, M. Mennenga, and C. Herrmann, “Factors influencing the energy intensity of automotive manufacturing plants,” *Journal of Cleaner Production*, vol. 2011, 2016.
- [150] International Energy Agency, “Energy Efficiency Indicators: Essentials for Policy Making,” 2014.
- [151] L. Meng, M. Zhou, C. Zhang, and G. Tian, “A New Model for Predicting Power Consumption of Machining Processes: A Turning Case,” in *2016 IEEE International Conference on Automation Science and Engineering*, 2016, pp. 1289–1294.
- [152] T. Devoldere, W. Dewulf, W. Deprez, B. Willems, and J. R. Duflou, “Improvement Potential for Energy Consumption in Discrete Part Production Machines,” in *Proceedings of the 14th CIRP Conference on Life Cycle Engineering*, 2007, pp. 311–316.
- [153] W. Reitler, M. Rudolph, and H. Schaefer, “Analysis of the factors influencing energy consumption in industry,” *Energy Economics*, vol. 9, no. 3, pp. 145–148, 1987.
- [154] J. N. Plessis, R. Pelzer, and J. C. Vosloo, “Sustaining the Performance of Diverse Energy Management Systems through Reactive Maintenance,” in *2015 International Conference on the Industrial and Commercial Use of Energy (ICUE)*, 2015.
- [155] Y. Nagata, “The US/Japan comparison of energy intensity. Estimating the real gap,” *Energy Policy*, vol. 25, no. 7–9, pp. 683–691, Jun. 1997.
- [156] A. B. Jaffe and R. N. Stavins, “The energy-efficiency gap What does it mean?,” *Energy Policy*, vol. 22, no. 10, pp. 804–810, Oct. 1994.
- [157] P. Do, A. Voisin, E. Levrat, and B. Iung, “A proactive condition-based maintenance strategy with both perfect and imperfect maintenance actions,” *Reliability Engineering & System Safety*, vol. 133, pp. 22–32, 2015.
- [158] G. May, I. Barletta, B. Stahl, and M. Taisch, “Energy management in production: A novel method to develop key performance indicators for improving energy efficiency,” *Applied Energy*, vol. 149, pp. 46–61, 2015.

- [159] Y. Seow, S. Rahimifard, and E. Woolley, "Simulation of energy consumption in the manufacture of a product," *International Journal of Computer Integrated Manufacturing*, vol. 26, no. 7, pp. 663–680, 2013.
- [160] X. Chavanne and J.-P. Frangi, "Comparison of the energy efficiency to produce agroethanol between various industries and processes: Synthesis," *Biomass and Bioenergy*, vol. 35, no. 7, pp. 2737–2754, Jul. 2011.
- [161] J. Madan, M. Mani, J. H. Lee, and K. W. Lyons, "Energy Performance Evaluation and Improvement of Unit-Manufacturing Processes: Injection Molding Case Study," *Journal of Cleaner Production*, vol. 105, pp. 157–170, Sep. 2015.
- [162] J. K. Kaldellis and P. Fragos, "Ash deposition impact on the energy performance of photovoltaic generators," *Journal of Cleaner Production*, vol. 19, no. 4, pp. 311–317, Mar. 2011.
- [163] A. Voisin, E. Levrat, P. Cochetoux, and B. Iung, "Generic prognosis model for proactive maintenance decision support: Application to pre-industrial e-maintenance test bed," *Journal of Intelligent Manufacturing*, vol. 21, no. 2, pp. 177–193, 2010.
- [164] J. Z. Sikorska, M. Hodkiewicz, and L. Ma, "Prognostic modelling options for remaining useful life estimation by industry," *Mechanical Systems and Signal Processing*, vol. 25, no. 5, pp. 1803–1836, 2011.
- [165] L. Liao and F. Kottig, "Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction," *IEEE Transactions on Reliability*, vol. 63, no. 1, pp. 191–207, 2014.
- [166] D. An, N. H. Kim, and J.-H. Choi, "Practical options for selecting data-driven or physics-based prognostics algorithms with reviews," *Reliability Engineering & System Safety*, vol. 133, pp. 223–236, Jan. 2015.
- [167] D. A. Tobon-Mejia, K. Medjaher, N. Zerhouni, and G. Tripot, "A data-driven failure prognostics method based on mixture of Gaussian hidden Markov models," *IEEE Transactions on Reliability*, vol. 61, no. 2, pp. 491–503, 2012.
- [168] M. Shafiee, M. Finkelstein, and C. Bérenguer, "An opportunistic condition-based maintenance policy for offshore wind turbine blades subjected to degradation and environmental shocks," *Reliability Engineering & System Safety*, vol. 142, pp. 463–471, 2015.
- [169] M. Bengtsson and M. Kurdve, "Machining Equipment Life Cycle Costing Model with Dynamic Maintenance Cost," *Procedia CIRP*, vol. 48, pp. 102–107, 2016.

- [170] a. Grall, C. Bérenguer, and L. Dieulle, “A condition-based maintenance policy for stochastically deteriorating systems,” *Reliability Engineering and System Safety*, vol. 76, no. 2, pp. 167–180, 2002.
- [171] P. N. Muchiri, L. Pintelon, H. Martin, and P. Chemweno, “Modelling maintenance effects on manufacturing equipment performance: results from simulation analysis,” *International Journal of Production Research*, vol. 52, no. 11, pp. 3287–3302, 2013.
- [172] R. Fritzsche, J. N. D. N. D. Gupta, and R. Lasch, “Optimal prognostic distance to minimize total maintenance cost: The case of the airline industry,” *International Journal of Production Economics*, vol. 151, pp. 76–88, Feb. 2014.
- [173] W. Jin *et al.*, “Development and Evaluation of Health Monitoring Techniques for Railway Point Machines,” in *Prognostics and Health Management (PHM), 2015 IEEE Conference on*, 2015, p. 11.
- [174] A. Hoang, P. Do, B. Iung, E. Levrat, and A. Voisin, “Performance d’efficacité énergétique: concepts et pronostic,” in *10 ème Conférence Francophone de Modélisation, Optimisation et Simulation- MOSIM’14*, 2014, p. 107.
- [175] L. Zhou, J. Li, F. Li, Q. Meng, J. Li, and X. Xu, “Energy consumption model and energy efficiency of machine tools: a comprehensive literature review,” *Journal of Cleaner Production*, vol. 112, pp. 3721–3734, 2015.
- [176] J. Farla, K. Blok, and L. Schipper, “Energy efficiency developments in the pulp and paper industry,” *Energy Policy*, vol. 25, no. 7–9, pp. 745–758, 1997.
- [177] G. Zhou, W. Chung, and Y. Zhang, “Measuring energy efficiency performance of China’s transport sector: A data envelopment analysis approach,” *Expert Systems with Applications*, vol. 41, no. 2, pp. 709–722, Feb. 2014.
- [178] K. Mukherjee, “Energy use efficiency in U.S. manufacturing: A nonparametric analysis,” *Energy Economics*, vol. 30, no. 1, pp. 76–96, Jan. 2008.
- [179] F. Sloukia, M. El Aroussi, H. Medromi, and M. Wahbi, “Bearings prognostic using Mixture of Gaussians Hidden Markov Model and Support Vector Machine,” *International Journal of Network Security & Its Applications (IJNSA)*, vol. 5, no. 3, pp. 1–4, 2013.
- [180] G. Medina-oliva, A. Voisin, M. Monnin, J. Leger, and B. Iung, “Key factor identification for energy consumption analysis,” in *European conference of the Prognostics and Health Management society 2014*, 2014.
- [181] G. Vinson, P. Ribot, and M. Combacau, “A generic ageing model for prognosis -

- Application to Permanent Magnet Synchronous Machines,” in *Second European Conference of the Prognostics and Health Management Society 2014*, 2014, pp. 1–11.
- [182] Y. Peng, M. Dong, and M. J. Zuo, “Current status of machine prognostics in condition-based maintenance: a review,” *The International Journal of Advanced Manufacturing Technology*, vol. 50, no. 1–4, pp. 297–313, Jan. 2010.
- [183] K. Medjaher, H. Skima, and N. Zerhouni, “Condition assessment and fault prognostics of microelectromechanical systems,” *Microelectronics Reliability*, vol. 54, no. 1, pp. 143–151, Jan. 2014.
- [184] A. Kusiak, F. Tang, and G. Xu, “Multi-objective optimization of HVAC system with an evolutionary computation algorithm,” *Energy*, vol. 36, no. 5, pp. 2440–2449, May 2011.
- [185] K. Goebel, B. Saha, and A. Saxena, “A comparison of three data-driven techniques for prognostics,” in *62nd Meeting of the Society for Machinery Failure Prevention Technology*, 2008, pp. 1–13.
- [186] S. Sankararaman and K. Goebel, “An Uncertainty Quantification Framework for Prognostics and Condition-Based Monitoring,” in *16th AIAA Non-Deterministic Approaches Conference*, 2014, pp. 1–9.
- [187] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou, “Remaining useful life estimation – A review on the statistical data driven approaches,” *European Journal of Operational Research*, vol. 213, no. 1, pp. 1–14, Aug. 2011.
- [188] M. Lebold and M. Thurston, “Open standards for condition-based maintenance and prognostic systems,” in *Maintenance and Reliability Conference (MARCON)*, 2001, vol. 200.
- [189] J. Lee, J. Ni, D. Djurdjanovic, H. Qiu, and H. Liao, “Intelligent prognostics tools and e-maintenance,” *Computers in Industry*, vol. 57, no. 6, pp. 476–489, Aug. 2006.
- [190] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, and D. Siegel, “Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications,” *Mechanical Systems and Signal Processing*, vol. 42, no. 1–2, pp. 314–334, Jan. 2014.
- [191] A. Hoang, P. Do, B. Iung, E. Levrat, and A. Voisin, “Prognostics and Energy Efficiency : Survey and Investigations,” in *European Conference of the Prognostics and Health Management Society 2014*, 2014, pp. 147–161.
- [192] B. Iung, E. Levrat, A. C. Marquez, and H. Erbe, “Conceptual framework for e-Maintenance: Illustration by e-Maintenance technologies and platforms,” *Annual*

- Reviews in Control*, vol. 33, no. 2, pp. 220–229, 2009.
- [193] A. Hoang, P. Do, and B. Iung, “Energy efficiency performance-based prognostics for aided maintenance decision-making: Application to a manufacturing platform,” *Journal of Cleaner Production*, vol. 142, pp. 1–20, 2016.
- [194] A. Hoang, P. Do Van, B. Iung, E. Levrat, and A. Voisin, “Considération d’un indicateur d’efficacité énergétique pour la prise de décision en maintenance : de sa définition au fondement de son pronostic,” *Journal Européen des Systèmes Automatisés (JESA)*, vol. 49, no. 4–5, pp. 559–578, 2016.
- [195] M. Irfan, N. Saad, R. Ibrahim, and V. S. Asirvad, “Development of an Intelligent Condition Monitoring System for AC C Induction Motors using PLC,” *Business Engineering and Industrial Applications Colloquium (BEIAC), 2013 IEEE*, pp. 789–794, 2013.
- [196] J. M. Van Noortwijk, “A survey of the application of gamma processes in maintenance,” *Reliability Engineering and System Safety*, vol. 94, no. 1, pp. 2–21, 2009.
- [197] C. Ritz and J. C. Streibig, *Nonlinear Regression with R*. Springer Science & Business Media, 2008.
- [198] A. Hoang, P. Do, and B. Iung, “Prognostics on Energy Efficiency Performance for Maintenance Decision-Making: Application to Industrial Platform TELMA,” in *2015 Prognostics and System Health Management Conference-Beijing (2015 PHM-Beijing)*, 2015.
- [199] N. Tchertchian and D. Millet, “Eco-maintenance for complex systems: Application on system of renewable energy production,” *3rd International Symposium on Environmental Friendly Energies and Applications (EFEA)*, pp. 1–7, 2014.
- [200] M. Dörr, S. Wahren, and T. Bauernhansl, “Methodology for Energy Efficiency on Process Level,” *Procedia CIRP*, vol. 7, pp. 652–657, Jan. 2013.
- [201] A. Dietmair, A. Verl, and P. Eberspacher, “Model-based energy consumption optimisation in manufacturing system and machine control,” *International Journal of Manufacturing Research*, pp. 226–233, Oct. 2011.
- [202] G. May, B. Stahl, M. Taisch, and D. Kiritsis, “Energy management in manufacturing: From literature review to a conceptual framework,” *Journal of Cleaner Production*, pp. 1–26, 2016.
- [203] S. Lee, M.-C. Teng, K. Fan, K. Yang, and R. S. Horng, “Application of an energy management system in combination with FMCS to high energy consuming IT industries

- of Taiwan,” *Energy Conversion and Management*, vol. 52, no. 8–9, pp. 3060–3070, Aug. 2011.
- [204] A. Hoang, P. Do, and B. Iung, “Integrating Energy Efficiency-Based Prognostic Approaches into Energy Management Systems of Base Stations,” in *The 2014 International Conference on Advanced Technologies for Communications (ATC’14)*, 2014, pp. 220–225.
- [205] K. Abdennadher, P. Venet, G. Rojat, J. M. Rétif, and C. Rosset, “A real-time predictive-maintenance system of aluminum electrolytic capacitors used in uninterrupted power supplies,” *IEEE Transactions on Industry Applications*, vol. 46, no. 4, pp. 1644–1652, 2010.
- [206] J. Sun, H. Zuo, W. Wang, and M. G. Pecht, “Prognostics uncertainty reduction by fusing on-line monitoring data based on a state-space-based degradation model,” *Mechanical Systems and Signal Processing*, vol. 45, no. 2, pp. 396–407, Apr. 2014.
- [207] W. Kahlenborn, S. Kabisch, J. Klein, I. Richter, and S. Schürmann, “Energy Management - Systems in Practice,” *Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU)*, 2012. .
- [208] M. Neelis, E. Worrell, and E. Masanet, “Energy Efficiency Improvement and Cost Saving Opportunities for the Petrochemical industry An ENERGY STAR ® Guide for Energy and Plant Managers,” 2008.
- [209] P. Do Van, A. Barros, C. Bérenguer, K. Bouvard, and F. Brissaud, “Dynamic grouping maintenance with time limited opportunities,” *Reliability Engineering & System Safety*, vol. 120, pp. 51–59, Dec. 2013.
- [210] S. Ross, *Stochastic Processes. Wiley Series in Probability and statistics*. John Wiley & Sons, Inc., 1996.
- [211] A. Hoang, P. Do, and B. Iung, “Investigation on the use of energy efficiency for condition-based maintenance,” in *The 3rd IFAC AMEST workshop*, 2016.

Résumé de la thèse en Français

De nos jours, « la gestion de l'énergie » est la clé de la croissance économique en lien avec les entreprises de biens et de services. En effet par exemple, les entreprises industrielles ayant des activités complexes de production, de fourniture de service, consomment une quantité énorme d'énergie qui engendrent des coûts additionnels très importants. Par conséquent, l'optimisation énergétique des installations industrielles (machine outils, ligne d'assemblage, fours, processus continu ...) est un défi majeur pour assurer leur compétitivité économique tout en minimisant leur impact sur l'environnement. Ceci est d'autant plus vrai pour les nouveaux systèmes de production (manufacturier) tels que préconisé par l'Industrie 4.0 ou « l'Usine du futur » qui sont organisés selon différents niveaux d'abstraction, chacun structuré autour de nombreux composants hétérogènes (ex. logiciels, matériel, humains ...), interagissant entre eux de façon complexe pour réaliser la mission du système. Cette vision multi-niveaux et la complexité inhérente conduisent à une maîtrise et une optimisation de l'énergie difficiles à assurer alors que ce sont une voie de succès pour garantir la durabilité des systèmes (au sens développement durable). Cette dernière peut être appréhendée principalement en considérant l'Efficacité Énergétique (EE) comme un indicateur de performance clé (KPI) pour piloter ces systèmes, à savoir réduire la quantité d'énergie requise pour fournir des produits et des services. Cette considération est bien en phase avec un challenge phare de l'union européenne (UE) parce que l'Europe a fixé des objectifs ambitieux pour promouvoir le développement de nouvelles méthodologies, de nouvelles technologies améliorant l'efficacité énergétique et réduisant les coûts énergétiques jusqu'à 20% dans les secteurs industriels les plus consommateurs en énergie (fabrication de verre, de ciment, d'acier, de raffinage ...) [1].

Ce challenge doit donc induire une reconsidération dans la façon de contrôler les systèmes industriels non seulement en regards des performances ou des services conventionnels (par exemple, la fiabilité, la productivité), mais aussi de ceux émergents tels que ceux représentatifs des exigences de développement durable [2] - [4]. Par conséquent, en intégrant de nouveaux KPIs de durabilité, tels que l'EE, dans le processus décisionnel des systèmes industriels, la performance devrait être maîtrisée et optimisée conjointement en ce qui concerne les trois piliers fondamentaux : l'économie, l'environnement et la société. Dans le domaine manufacturier, ces piliers ont permis de promouvoir les cadres de réflexion autour de la "Fabrication verte", la "Production verte". Néanmoins, cet indicateur d'EE n'est pas vraiment associé aujourd'hui à la prise de décision dans l'industrie.

Plusieurs raisons peuvent expliquer cette dernière affirmation. Les travaux actuels sur l'EE se focalisent principalement sur les propriétés d'EE isolées (par exemple, la consommation d'énergie, l'économie

d'énergie) sans définir clairement le concept dans son ensemble et comment mesurer vraiment les indicateurs d'efficacité énergétique (EEI). En effet, même si certaines méthodes d'évaluation de l'EEI existent, elles concernent principalement les valeurs d'EEI au niveau des composants (niveau opérationnel), sans l'envisager (par exemple par agrégation) au niveau du système qui est un niveau nécessaire pour une optimisation réussie des performances dans une vision holistique (niveau stratégique) [5], [6]. En outre, cette évaluation n'est pas facile à faire car elle doit tenir compte de la dynamique du système (âge, dégradation, différents profils de fonctionnement, des conditions opérationnelles, etc.), impactant la valeur d'EEI et amenant à suivre son évolution dans le futur pour définir clairement la Performance de l'Efficacité Énergétique (EEP). La Performance EE est une performance qui révèle si le système industriel est efficace ou non (c'est plus qu'une valeur, c'est la valeur dans le temps). La formulation de l'EEI et de l'EEP n'est pas évidente [7], en particulier en ce qui concerne le contexte dynamique (ex. changement d'état des systèmes) pour prédire l'évolution de l'EE dans la même logique qu'est prédit la Durée de Vie Résiduelle (RUL) des composants par l'utilisation d'approches classiques de pronostic [8] - [11]. Ainsi, un défi important dans le développement de ces formulations est « *Comment définir, évaluer et prévoir ces EEI/EEP aux différents niveaux d'abstraction d'un système industriel (plus spécifiquement un système manufacturier) en considérant la dynamique de ce système ?* » (Défi n°1).

Les résultats de ces formalisations peuvent être intégrés dans un second temps dans les processus de prise de décision afin de maîtriser l'EEI/EEP le plus près possible de sa valeur nominale, pour le contrôle du pilier environnemental. Plus précisément, cette exigence de maîtrise peut être mise en œuvre par le processus d'aide à la décision de maintenance comme préconisé par la communauté Prognostics and Health Management (PHM) [12] - [14]. En effet, une stratégie de maintenance efficace pourrait non seulement éviter la défaillance du système, mais aussi permettre d'anticiper l'évolution de sa consommation d'énergie. Néanmoins, les décisions actuelles de maintenance reposent principalement sur des indicateurs conventionnels tels que la fiabilité, la disponibilité, le coût direct, etc. [15], et seules quelques recherches ont été réalisées pour considérer les relations entre EEI et la stratégie de maintenance [10] [16], [17]. Cette relation est une réelle opportunité pour une évolution voire une rupture dans la philosophie maintenance puisque la « condition » pour déclencher l'action de maintenance serait définie principalement sur les exigences de durabilité et l'évolution de leurs valeurs (pour promouvoir l'originalité vers l'EEP). Ceci serait d'autant plus vrai pour la stratégie de type conditionnelle/prévisionnelle telle que défendue par le CBM (Condition-Based Maintenance). Ceci conduit à s'attaquer à un deuxième défi important qui est « *Comment utiliser l'EE dans les stratégies de CBM ?* » (Défi n°2).

En résumé, en se référant aux deux challenges précédemment définis, l'idée fondamentale, que nous défendons dans cette thèse, est liée à l'évolution nécessaire de la maintenance et plus précisément de la

CBM pour intégrer l'efficacité énergétique (EE) en termes d'indicateur EE (EEI) et de sa durée de vie résiduelle (concept de REEL ; durée de vie résiduelle de l'efficacité énergétique), dans la phase de prise de décision. Ces deux concepts d'EE sont représentatifs des exigences de développement durable requises par le système industriel pour satisfaire aux 3 piliers. Cette idée se structure sur deux grandes orientations scientifiques : La première est liée au fondement du concept d'EEI et de son évaluation/prévision (EEP) en ce qui concerne le fonctionnement du système industriel. Ceci se réfère à plusieurs questions scientifiques comme : *Définition et formalisation de l'indicateur de l'efficacité énergétique - EEI utilisable dans le processus de prise de décision du système industriel (problème scientifique n ° 1); Définition et formulation de la performance d'efficacité énergétique (EEP) pour estimer la REEL d'un composant/fonction/système (Question scientifique n ° 2); Développement d'une approche générique pour aider le déploiement de pronostics afin de prédire l'évaluation de l'EEI à différents niveaux du système de production (Question scientifique n ° 3)*. La deuxième orientation concerne le principe d'intégration de l'EE dans la prise de décision en maintenance et le contrôle de la performance obtenue. Ceci se réfère à une autre question scientifique qui est le *Fondement de la politique de maintenance CBM basée sur l'EE (problème scientifique n ° 4)*.

Ces problèmes scientifiques ont été abordés au cours de cette thèse pour donner naissance à cinq contributions principales: (1) Définition d'un concept EEI pertinent au niveau composant/fonction/système d'un système de production (manufacturier); (2) Proposition d'une formulation générique pour pouvoir calculer l'EEI (et son évolution) en tenant compte des facteurs statiques et dynamiques du système à chaque niveau d'abstraction; (3) Proposition d'un concept EEP, à partir du concept REEL (durée de vie résiduelle de l'efficacité énergétique), représentatif de l'évolution de l'EEI, et donc du temps restant avant qu'un système perde ses propriétés énergétiques (franchissement du seuil de non performance); (4) Élaboration d'une approche générique construite à partir de différentes étapes et permettant d'aboutir à la formulation de l'EEI dans un cas industriel spécifique; (5) Investigation sur l'utilisation de l'EE dans la prise de décision de maintenance et plus spécifiquement pour le CBM.

Ces 6 contributions sont discutées, construites au travers de 6 chapitres :

Le chapitre 1 dresse une vue d'ensemble sur comment la durabilité (sustainability) est considérée dans le processus décisionnel, plus spécifiquement celui mis en œuvre par la fonction maintenance du système industriel (de production) [18] - [21]. Ainsi, ce chapitre débute par un état de l'art sur le développement durable en général, en soulignant ses trois principaux piliers et les principaux indicateurs de performance (KPI) de chaque pilier. En outre, l'utilisation de ces KPI dans le domaine industriel, principalement le manufacturier (fabrication/production), est étudiée. Cela conduit à se focaliser sur les éléments de l'EE tels que l'EEI et l'EEP, dans le processus de prise de décision en maintenance. Cette considération vise à isoler

les deux principaux défis industriels liés à l'intérêt de formaliser clairement l'EEI/EEP à différents niveaux d'un système manufacturier et l'intégration de l'EE dans une politique CBM.

A partir du positionnement précédent, le chapitre 2 identifie les problèmes scientifiques liés à chacun des deux défis. Ainsi, le chapitre 2 se focalise d'abord sur la définition et la mesure de l'EE, mais aussi sa prédiction pour être utilisable dans la prise de décision en maintenance surtout dans le cadre d'une stratégie de type CBM (exploitation d'une condition déclenchant l'action) [22], [23]. Cela conduit à souligner les problèmes liés au développement des concepts d'EEI cohérents et pertinents à plusieurs niveaux d'abstraction d'un système industriel, mais aussi à la formulation générique de l'EEI prenant en compte la dynamique du système (en termes de facteurs d'impact génériques) (*Question scientifique n°1*). Cette formulation se doit d'intégrer des conditions temporelles pour proposer tout l'ensemble des variables utilisables dans la prédiction de l'évolution de l'EEI. Cette évolution de l'EEI est directement liée à l'étude de l'évaluation de l'EEP en termes d'énergie résiduelle (*Question scientifique n°2*). Ensuite, les formulations génériques doivent être détaillées selon une démarche spécifique pour permettre un calcul EEI concret (au temps t), mais aussi le suivi de son évolution. Cette concrétisation se doit d'être développée à partir d'une approche générique (*Question scientifique n°3*) intégrant toutes les étapes de la sélection des facteurs d'impact spécifiques jusqu'à l'évaluation EEP.

Enfin, pour garder l'EEI/EEP aussi proches que possible de leurs valeurs optimales, l'évolution de la stratégie de maintenance doit être étudiée pour intégrer ces indicateurs comme condition pour déclencher la maintenance comme préconisé plus conventionnellement par le CBM (*Question scientifique n°4*). Ces 4 questions scientifiques sont abordées dans les chapitres suivants pour présenter les contributions de la thèse.

Plus précisément, le chapitre 3 a pour objet de décrire les contributions liées aux deux premiers problèmes scientifiques. En ce sens, la première contribution concerne le fondement d'un concept EEI approprié pour le système manufacturier (classe spécifique de système industriel) et utilisable à différents niveaux d'abstraction de ce système [24]. Ce fondement comprend la définition générique de l'EEI basée sur deux aspects principaux des propriétés de l'EE : la consommation d'énergie et la production utile (la sortie du système). Ces deux propriétés représentent des variables à maîtriser dans le processus décisionnel. En outre, une formulation générique d'EEI, utilisable à chaque niveau, est proposée. Cette formulation est décrite comme le rapport entre deux parties dans lesquelles les facteurs dépendants du temps (appelés facteurs statiques et dynamiques) sont considérés. La première partie concerne les différents types de ressources énergétiques consommées (comme entrées). La deuxième partie concerne les produits fabriqués fournis (en tant que produits de sortie) [25]. La formulation peut être utile pour un système manufacturier spécifique afin de calculer la valeur de l'EEI et aussi l'évolution de l'EEI (en raison des facteurs dépendants du temps).

Enfin, en ce qui concerne le deuxième problème scientifique, il est proposé un nouveau concept appelé REEL (Durée de vie restante de l'efficacité énergétique) basé sur l'évolution de l'EEI et représentant la durée à partir de l'instant présent (dans la zone d'efficacité) jusqu'au moment où le système manufacturier va fonctionner dans une zone de non-efficacité énergétique. Le REEL est à considérer comme équivalent à l'EEP pour présenter une propriété importante de l'EE du système manufacturier (pour évaluer le temps restant avant qu'un composant/fonction/système ne perde ses propriétés énergétiques sous un seuil limite).

Le chapitre 4 a pour objectif d'aborder la question scientifique $n^{\circ}3$ à travers une approche permettant de mettre en œuvre différentes étapes nécessaires pour utiliser la formulation générique du calcul de l'EEI sur un système de manufacturier spécifique, puis pour évaluer le REEL.

Ainsi, il est proposé une approche générique structurée sur 3 étapes principales. Dans la première étape, il est prévu de définir clairement, à chaque niveau du système manufacturier spécifique, la consommation d'énergie (en entrée) et le produit manufacturé utile (en sortie). Pour bien comprendre le processus de transformation des entrées en sorties, un diagramme de flux d'énergie et un diagramme de production doivent être fournis à l'avance (par des experts) [26]. Ensuite, sont identifiés les composants en aval qui peuvent avoir une forte contribution sur l'EEI au niveau supérieur. Il est également déterminé, pour chaque niveau, les facteurs d'impact (statique et dynamique) qui doivent être pris en compte. Des modèles existants sont ensuite investigués en regard de l'intégration des facteurs identifiés afin de les utiliser pour chaque partie de la formulation (consommation d'énergie, sortie). Si un modèle approprié pour la consommation d'énergie et/ou la sortie n'est pas disponible, les modèles se doivent d'être créés. Enfin, à partir de tous les modèles, des formulations spécifiques (modèles EEI) sont développées à chaque niveau pour calculer la valeur EEI correspondante (au temps t).

La deuxième étape de la procédure est consacrée à sélectionner et à mettre en œuvre la méthode de pronostic la plus appropriée pour prédire l'évolution de chaque facteur d'impact. Ainsi, la totalité de ces évolutions obtenues à la fin de cette étape sont réintégrées, à la troisième étape, dans les formulations spécifiques (exprimées à l'étape 1) pour évaluer cette fois-ci, la valeur EEI à tout moment dans le futur (Evolution de l'EEI). À partir de cette évolution de l'EEI, il est évalué le temps restant avant que le système ne perde ses propriétés d'énergie sous un seuil limite (calcul REEL).

Le chapitre 5 a pour objet de valider les contributions proposées aux chapitres 3 et 4 en les appliquant sur la plate-forme TELMA. TELMA est une plate-forme qui matérialise un processus physique dédié au déroulement d'une bande type métal, papier etc. Ce processus est similaire aux applications industrielles telles que la coupe de tôle et la coupe de bobines de papier. Le processus physique de TELMA est divisé en quatre parties : changement de bobines, accumulation de bande, coupe-poinçonnage et système d'avance. Chaque partie se compose de plusieurs composants tels que des vérins, le mandrin, le système de

marquage, des moteurs, etc. Cette première étape de la phase de validation est principalement focalisée sur les deux moteurs indépendants qui interviennent dans la fonction "poinçonnage" (Moteur consommant uniquement de l'énergie électrique) [27]. Ainsi, les modèles EEI issus de la mise en œuvre de la première étape de l'approche générique (chapitre 4) sont construits à partir des données de terrain acquises sur les moteurs (un modèle EEI par moteur) complétées par des données relatives à la fonction réalisée par ces moteurs (un modèle EEI de la fonction). Ces modèles intègrent des facteurs d'impact tels que la détérioration des roulements (facteur dynamique) et le profil de la mission (facteur statique) [28] - [31]. Ainsi, les approches de pronostics basés sur les données sont choisies pour prédire l'évolution de la détérioration des roulements (facteur dynamique), alors que le profil de la mission est fixé à l'avance en considérant le plan de production (facteur statique). Ces évolutions de facteurs permettent de calculer l'évolution de l'EEI pour chaque moteur ainsi que pour la fonction considérée conduisant à évaluer le REEL de ces éléments. Les résultats obtenus à partir de ces modèles ont démontré que l'EEI peut être calculé à tout moment et que l'évolution de l'EE (valeurs REEL) peut être prédite à la fois au niveau des composants (moteurs) et au niveau de la fonction dans le cadre d'un système spécifique.

Le chapitre 6 traite enfin la question scientifique $n^{\circ}4$ en étudiant l'intérêt d'intégrer l'EE dans la prise de décision en CBM. L'investigation se concentre principalement sur la proposition d'un nouveau modèle CBM basé sur l'EE en utilisant la valeur EEI comme condition (et pas encore la valeur EEP) pour déclencher l'action de maintenance prévisionnelle. Ainsi, l'idée principale de ce CBM basé sur l'EEI est d'inspecter, à un moment précis, la consommation d'énergie ainsi que les valeurs de sortie du système, puis de calculer l'EEI et de déclencher ou non des actions. En effet, une action de maintenance est déclenchée si la valeur EEI est supérieure à un seuil préventif. L'intervalle de temps d'inspection et les seuils préventifs sont des paramètres de décision à optimiser. Il est considéré ensuite soit la valeur EEI de chaque composant individuel soit la valeur EEI d'un groupe de composants au niveau de la fonction/système (comme le permettent les formalisations de l'EEI au chapitre 3), pour proposer deux stratégies principales de CBM (appelées maintenance individuelle ; regroupement d'actions de maintenance ou maintenance opportuniste). Dans le but de comparer les avantages de cette nouvelle stratégie CBM basée sur l'EEI avec une approche CBM conventionnelle, une extension d'un modèle de coût existant de CBM a été effectuée en prenant en compte non seulement les coûts de maintenance, mais aussi le coût de l'énergie. Le modèle étendu conduit à considérer l'énergie directement dans l'optimisation de la maintenance. L'étape de comparaison est développée sur l'étude de cas de la plate-forme TELMA permettant d'évaluer l'impact de l'EE sur les stratégies CBM existantes et de conclure sur les intérêts d'une nouvelle pratique CBM basée sur l'EE en termes d'optimisation des coûts. En effet, uniquement au niveau du moteur, les résultats du calcul de l'EEI sont utilisés pour la mise en œuvre du CBM basé sur l'EEI. De cette façon, la technique de simulation de Monte Carlo a été appliquée pour trouver le temps de remplacement du premier composant

[32]. Ce temps a été utilisé dans le modèle étendu pour calculer le coût conduisant à sélectionner les paramètres optimaux (intervalle d'inspection et seuil EEI) en minimisant ce coût. Parallèlement, une stratégie CBM conventionnelle a été appliquée en considérant le niveau de détérioration du roulement comme condition. Ensuite, les mêmes outils (ex. Monte Carlo, modèle étendu) ont été utilisés pour décider des paramètres optimaux. La comparaison des 2 coûts minimisés a montré que le CBM basé sur l'EEI est une politique efficace lorsque la quantité de consommation d'énergie est élevée. Ceci est toujours vrai lorsque l'analyse de la sensibilité se fait en modifiant le coût de l'inspection, le coût de maintenance préventive, les prix de l'énergie et le comportement de détérioration d'un facteur d'impact dynamique (la dégradation du roulement). Ainsi dans ce contexte d'expérimentation, l'intérêt d'une nouvelle pratique CBM fondée sur l'EEI a été mis en évidence.

Par rapport à tout ce travail de thèse, les principales originalités revendiquées sont : la prise en compte de l'EE dans les systèmes manufacturiers comme un KPI pour faire face aux problèmes de durabilité ; la construction de l'EEI ; la proposition du nouveau concept de REEL pour considérer l'évolution de l'EEI dans la prise de décision (EEP) ; l'étude d'une nouvelle stratégie CBM basée sur l'EE(I) pour laquelle la condition à maîtriser est axée sur la durabilité. La plupart de ces contributions sont génériques et peuvent donc être émises pour différents types de systèmes manufacturiers et à chaque niveau d'abstraction de ces systèmes.

Cependant, les contributions apportées au cours de cette thèse ne couvrent pas toutes les réponses attendues en ce qui concerne les deux défis. Ainsi, certaines perspectives peuvent être émises telles que :

- L'extension du contexte de validation pour prouver la faisabilité et les la valeur ajoutée réels des contributions (CBM basée sur l'EE) dans le cadre d'un véritable système industriel (par exemple, une possibilité est de les appliquer sur une presse à l'usine RENAULT située à Flins).
- Le développement d'un « modèle EE générique » utilisable pour la classe de système manufacturier. Ce modèle doit être une concrétisation de la formulation textuelle proposée au chapitre 3 (par exemple, la formalisation des connaissances sur les ressources énergétiques - les intrants, les résultats, les facteurs d'impact, les relations et les règles entre eux, les pronostics sur les facteurs d'impact, etc.). Ce modèle devrait permettre de définir un modèle d'EE particulier pour un composant spécifique, une fonction spécifique ... en mettant en œuvre une procédure d'instanciation.
- La mise en œuvre du CBM basé sur le REEL (EEP) qui doit être considérée comme une extension du CBM EEI actuel.

- La considération d'autres KPI de durabilité que l'EE, mais aussi des KPI classiques et de toutes les relations entre ces différents KPI dans le processus décisionnel de maintenance.
- Le développement d'une approche multicritères pour optimiser le processus de prise de décision en maintenance à partir de considérations à la fois des KPI conventionnels (par exemple le RUL) et de durabilité (EE, mais pas seulement, par exemple REEL, EEI, CO2) interagissant en termes d'impacts positifs ou négatifs.

Bibliographie

- [1] European Commission, "Energy challenges and policy," *European Commission*, 2013. .
- [2] G. Liu, "Development of a general sustainability indicator for renewable energy systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 611–621, Mar. 2014.
- [3] V. V. Prabhu, D. Trentesaux, and M. Taisch, "Energy-aware manufacturing operations," *International Journal of Production Research*, vol. 53, no. 23, pp. 6994–7004, 2015.
- [4] K. E. K. Vimala, S. Vinodha, and R. Muralidharan, "An approach for evaluation of process sustainability using multi-grade fuzzy method," *International Journal of Sustainable Engineering*, vol. 8, no. April, pp. 40–54, 2015.
- [5] A. V. H. Sola, C. M. D. M. Mota, and J. L. Kovaleski, "A model for improving energy efficiency in industrial motor system using multicriteria analysis," *Energy Policy*, vol. 39, no. 6, pp. 3645–3654, Jun. 2011.
- [6] J. R. Duflou *et al.*, "Towards energy and resource efficient manufacturing: A processes and systems approach," *CIRP Annals - Manufacturing Technology*, vol. 61, no. 2, pp. 587–609, Jan. 2012.
- [7] M. Mora, J. Vera, C. Rocamora, and R. Abadia, "Energy Efficiency and Maintenance Costs of Pumping Systems for Groundwater Extraction," *Water Resources Management*, vol. 27, no. 12, pp. 4395–4408, 2013.
- [8] C. S. Byington, M. J. Roemer, and T. Galie, "Prognostic enhancements to diagnostic systems for improved condition-based maintenance [military aircraft]," in *Proceedings, IEEE Aerospace Conference, 2002*, vol. 6, pp. 6-2815-6–2824.
- [9] S. Sankararaman, M. Daigle, A. Saxena, and K. Goebel, "Analytical algorithms to quantify the uncertainty in remaining useful life prediction," *2013 IEEE Aerospace Conference*, pp. 1–11, Mar. 2013.
- [10] B. Saha, K. Goebel, S. Poll, and J. Christophersen, "A Bayesian Framework for Remaining Useful Life Estimation," *Proceedings of AAAI Fall Symposium: AI for Prognostics (Working Notes)*, pp. 1–6, 2007.
- [11] A. Saxena, J. Celaya, B. Saha, S. Saha, and K. Goebel, "Metrics for Offline Evaluation of Prognostic Performance," *International Journal of Prognostics and Health Management*, pp. 1–20, 2010.
- [12] N. S. Clements, "Introduction to Prognostics," *Presented at Annual Conference of the PHM Society Montreal, Canada*, 2011.
- [13] X. Lei, P. Sandborn, R. Bakhshi, A. Kashani-pour, and N. Goudarzi, "PHM Based Predictive Maintenance Optimization for Offshore Wind Farms," in *Prognostics and Health Management (PHM), 2015 IEEE*, 2015, pp. 1–8.
- [14] B. Zhang, L. Zhang, and J. Xu, "Degradation Feature Selection for Remaining Useful Life Prediction of Rolling Element Bearings," *Quality and Reliability Engineering International*, p. n/a-n/a, 2015.
- [15] B. Liu, Z. Xu, M. Xie, and W. Kuo, "A value-based preventive maintenance policy for multi-

- component system with continuously degrading components,” *Reliability Engineering & System Safety*, vol. 132, pp. 83–89, Dec. 2014.
- [16] W. Xu and L. Cao, “Energy efficiency analysis of machine tools with periodic maintenance,” *International Journal of Production Research*, no. March, pp. 1–13, Mar. 2014.
- [17] B. Darabnia and M. Demichela, “Maintenance an opportunity for energy saving,” *Chemical Engineering Transactions*, vol. 33, pp. 259–264, 2013.
- [18] R. M. C. Ratnayake, “Sustainable performance of industrial assets: the role of PAS 55-1&2 and human factors,” *International Journal of Sustainable Engineering*, vol. 6, no. 3, pp. 198–211, 2013.
- [19] S. N. Morioka and M. M. de Carvalho, “A Systematic Literature Review Towards a Conceptual Framework for Integrating Sustainability Performance into Business,” *Journal of Cleaner Production*, vol. 136, pp. 1–28, 2016.
- [20] R. A. R. Ghazilla, N. Sakundarini, S. H. Abdul-Rashid, N. S. Ayub, E. U. Olugu, and S. N. Musa, “Drivers and barriers analysis for green manufacturing practices in Malaysian smes: A preliminary findings,” *Procedia CIRP*, vol. 26, pp. 658–663, 2015.
- [21] A. M. Deif, “A system model for green manufacturing,” *Journal of Cleaner Production*, vol. 19, no. 14, pp. 1553–1559, 2011.
- [22] A. Fysikopoulos, D. Anagnostakis, K. Salonitis, and G. Chryssolouris, “An Empirical Study of the Energy Consumption in Automotive Assembly,” *45th CIRP Conference on Manufacturing Systems 2012*, vol. Procedia C, pp. 477–482, Jan. 2012.
- [23] S. Thiede, G. Bogdanski, and C. Herrmann, “A Systematic Method for Increasing the Energy and Resource Efficiency in Manufacturing Companies,” *Procedia CIRP*, vol. 2, pp. 28–33, Jan. 2012.
- [24] A. Hoang, P. Do, B. Iung, E. Levrat, and A. Voisin, “Performance d’efficacité énergétique: concepts et pronostic,” in *10 ème Conférence Francophone de Modélisation, Optimisation et Simulation- MOSIM’14*, 2014, p. 107.
- [25] A. Hoang, P. Do, B. Iung, E. Levrat, and A. Voisin, “Prognostics and Energy Efficiency : Survey and Investigations,” in *European Conference of the Prognostics and Health Management Society 2014*, 2014, pp. 147–161.
- [26] A. Hoang, P. Do, and B. Iung, “Integrating Energy Efficiency-Based Prognostic Approaches into Energy Management Systems of Base Stations,” in *The 2014 International Conference on Advanced Technologies for Communications (ATC’14)*, 2014, pp. 220–225.
- [27] A. Hoang, P. Do, and B. Iung, “Prognostics on Energy Efficiency Performance for Maintenance Decision-Making: Application to Industrial Platform TELMA,” in *2015 Prognostics and System Health Management Conference-Beijing (2015 PHM-Beijing)*, 2015.
- [28] B. Iung, E. Levrat, A. C. Marquez, and H. Erbe, “Conceptual framework for e-Maintenance: Illustration by e-Maintenance technologies and platforms,” *Annual Reviews in Control*, vol. 33, no. 2, pp. 220–229, 2009.
- [29] A. Hoang, P. Do, and B. Iung, “Energy efficiency performance-based prognostics for aided maintenance decision-making: Application to a manufacturing platform,” *Journal of Cleaner Production*, vol. 142, pp. 1–20, 2016.
- [30] A. Hoang, P. Do Van, B. Iung, E. Levrat, and A. Voisin, “Considération d’un indicateur d’efficacité énergétique pour la prise de décision en maintenance : de sa définition au fondement de son pronostic,” *Journal Européen des Systèmes Automatisés (JESA)*, vol. 49, no. 4–5, pp. 559–578, 2016.
- [31] C. Ritz and J. C. Streibig, *Nonlinear Regression with R*. Springer Science & Business Media, 2008.
- [32] A. Hoang, P. Do, and B. Iung, “Investigation on the use of energy efficiency for condition-based maintenance,” in *The 3rd IFAC AMEST workshop*, 2016.