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GRADUATION PROGRAM IN PRODUCTION AND SYSTEMS ENGINEERING

FLÁVIO PIECHNICKI

A SMART RCM FRAMEWORK TO SUPPORT DECISION-MAKING PROCESSES IN INDUSTRIAL MAINTENANCE

CURITIBA

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PhD thesis presented to the Graduate Program in Production and Systems Engineering, in the area of concentration: Modeling, Control and Automation of Systems, of the Polytechnic School, of the Pontifical Catholic University of Paraná, as a partial requirement to obtain a PhD degree in Production Engineering and Systems.

Supervisor: Prof. Dr. Eduardo de Freitas Rocha Loures
Co-supervisor: Prof. Dr. Eduardo Alves Portela dos Santos

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EXAMINING COMMITTEE

Professor Dr. Eduardo de Freitas Rocha Loures
Pontifical Catholic University of Paraná

Professor Dr. Eduardo Alves Portela dos Santos
Pontifical Catholic University of Paraná

Professor Dr. Max Mauro Dias Santos
Federal Technological University of Paraná – Campus Ponta Grossa

Professor Dr. Emerson Rigoni
Federal Technological University of Paraná – Campus Curitiba

Professor Dr. Fernando Deschamps
Pontifical Catholic University of Paraná

Curitiba, 05 de março de 2020.

This work is dedicated to God, omnipotent creator and inspirer;

to my family, especially my companion and patient wife, Evelyn,

to my mother and in memory of my father, examples of strength and faith,

to Eduardo's professors, for productive experiences and valuable teachings.

Wisdom must be intuitive reason

combined with scientific knowledge.

(ARISTOTLE, Nicomacheian Ethics, VI.7)

ABSTRACT

Amongst the contemporary maintenance methodologies used to increase the reliability of industrial systems is the Reliability Centered Maintenance (RCM), which is employed to ensure that any components of an asset or operating system maintain their functions with efficiency, performance, safety, quality and economy, without impacting on the environment. However, with the improvement in technology and the consequent increase in quantity and quality of information available in industrial systems, it is necessary to customize and optimize RCM program. Thus, it is important to review the traditional methodology, as its implementation stages have many information-dependent decision-making processes, which are predominantly qualitative and used without appropriate criteria, making it difficult to manage. The proper collection and treatment of qualitative information and the denser insertion of quantitative information from the PIS (Production Information System) and MIS (Maintenance Information System) support the RCM, improving the quality of decisions and enabling program dynamization. This transformation from a predominantly static to dynamic data structure makes it possible to make maintenance more predictive and operation more responsive to deviations in the behavior of plant assets. The dense and diversified data sources, included related to Industry 4.0 technology enablers, help decision support mechanisms to make the processes more responsive and smart, allowing to choose the most appropriate decisions. In this context, the present research proposes a Smart-RCM framework that fusion qualitative and quantitative information, used to analyze and improve decisions in a customized model deployment. The choice of the best indicators to be used in the implementation and evaluation of the RCM, as well as the formalization of the information for its better use in the decision-making are important to guarantee the success of the program. It is proposed to create the Decision-making Database (DMD), whose purpose is to store and make available dynamic information to support decision-making in the RCM program phases. By identifying trends and applying Data and Process Mining techniques, hidden patterns and relationships can be discovered. MCDM (Multi Criteria Decision-making) methods support the decisions in the RCM implementation. It is proposed a Smart-RCM approach, which provides a model for the collection and use of indicators, used as inputs in MCDMs, prioritizing and ranking the Maintenance Significant Items (MSIs) and selecting the appropriate maintenance strategy to be implemented. The Smart-RCM approach can provide visibility and agility in maintenance processes. Even companies that work with calendar-oriented maintenance planning can gain an advantage in business agility, capacity assurance, and more informed decision making by analyzing the available indicator data. Whether making a business case for new machines, changes to current maintenance plans, or modifying a contract for a major equipment or asset, organizations need the physical data available to support these decisions and a way to present them to superior level decision makers.

Key-words: Reliability Centered Maintenance, Decision-making, Data analysis, Industry 4.0, Smart Maintenance.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AHP	Analytic Hierarchy Process
AIAG	Automotive Industry Action Group
BSC	Balanced Score-Card
CA	Criticality Analysis
CBM	Condition Based Maintenance
CEV	Criticality, Efficiency and Viability
CMMS	Computerized Maintenance Management System
CPN	Colored Petri Nets
CR	Consistency Result
DD	Downtime Data
DMD	Decision-making Database
DMM	Decision-making Methods
EAM	Enterprise Asset Management
ELECTRE	Elimination and Choice Expressing Reality
FFA	Functional Failure Analysis
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
IDEF	Integration Definition for Function Modeling
IEC	International Electrotechnical Commission
IIoT	Industrial Internet of Things
IS	Information System
ISO	International Organization for Standardization
KPI	Key Performance Indicator
MA	Maintenance Analytics
MCDA	Multi Criteria Decision Analysis
MCDM	Multi Criteria Decision-making
MIS	Maintenance Information System
MMIS.	Maintenance Management Information System
MPI	Maintenance Performance Indicator
MSI	Maintenance Significant Item
MSS	Maintenance Strategy Selection

MTBF	Mean Time Between Failures
MTO	Man, Technology and Organization
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
OEE	Overall Equipment Effectiveness
PdM	Predictive Maintenance
PIS	Process Information System
PLC	Programmable Logic Controller
PM	Preventive Maintenance
PROMETHEE	Preference Ranking Organization Method for Enrich. of Evaluations
PRx	Prescriptive Maintenance
RAMS	Reliability, Availability, Maintainabilty and Security
RCM	Reliability Centered Maintenance
RM	Reactive Maintenance
RPN	Risk Priority Number
RTF	Run-To Failure
RTM	Real-Time Monitoring
SAE	Society of Automotive Engineers
SWOT	Strengths, Weaknesses, Opportunities, and Threats
TBM	Time-Based Maintenance
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TPM	Total Productive Maintenance
WO	Work Order
WCM	World Class Manufacturing

SUMMARY

1 INTRODUCTION

The current industrial systems need to ensure the availability and reliability of the equipment, in order to achieve the predefined goals and parameters in productive systems. In many manufacturing environments, the condition of the equipment or process has a significant impact on the quantity and quality of units produced [1]. In this context, the maintenance function aims to increase the equipment life, or at least the average time for the next failure, whose repair can be costly. Furthermore, it is expected that the maintenance policy be effective and reduce the frequency of job interruptions and your unwanted effects for the process as a whole.

Researchers around the world are striving to develop and apply new techniques and methodologies for the improvement of maintenance processes. The goal is to use them for optimal maintenance policies, impacting positively on MPI's (Maintenance Performance Indicators), increasing quality and performance and reducing costs. In this scenario, methods like Decision-making [2], Statistics [3], Failure analysis [4], Fuzzy logic [5], Modeling [6], among others are employed, in the most of the time, in isolation, addressing the use of tacit or explicit information, with qualitative or quantitative approaches. Some efforts are made to integrate information from maintenance collaboratively, exploring frameworks under aspects of maintenance function development [7,8].

Industrial systems have different levels of maturity, under human, technological and organizational aspects, requiring customized database models that can provide the maximum information available and generate an appropriate knowledge base. Companies must evolve from a classical data management approach to using information and knowledge as critical business assets. Quality practices and data management are still essential, but these practices must be improved to meet the demands of the environment and business, with an appropriate cost-benefit ratio.

In this context emerges the RCM methodology that provides a framework capable of reducing maintenance activities and costs related to them as far as possible without affecting the performance of the plant, product quality, safety or environmental integrity [9]. However, for the program success, aspects should be observed of each RCM approach and the specific variables of the industrial system selected. This perception becomes difficult for the diversity of technologies involved in MMIS

(Maintenance Management Information Systems), EAM (Enterprise Asset Management), existence or not of Industry 4.0 aspects, level of automation systems, organizational characteristics and the maintenance structure as a whole.

The organization should consider the monitoring, measuring, analyzing and evaluating needed to drive and support its decision making on improvement actions. When deciding what to measure, how to measure, what to analyze, etc., it is important for the organization to understand what type of behavior and actions it wants to achieve from the asset management objectives before implementing them. The asset management objectives should be aligned to the organizational objectives and should promote collaboration with stakeholders.

According to the ISO 50002 standard [10] the asset management objectives should be specific, measurable, achievable, realistic and time-bound (i.e. “SMART” objectives). They can be both quantitative measurements (e.g. mean time between failure) and qualitative measurements (e.g. customer satisfaction).

The smart concept has been diffused in the literature under influence of the advances in context of Industry 4.0. Smart refers to systems that advance in communication and information technology to increase the degree of automation and digitization of production, manufacturing and industrial processes. The ultimate goal is to manage the entire value chain process, improving efficiency in the production process and obtaining superior products and services.

Thus, by linking maintenance management to the information context in the industry scenario 4.0, the need for adjustments in the traditional RCM methodology models is noticeable. In their implementation models, the decision-making processes have gaps regarding the quality and availability of information used. Available data needs to be better treated and structured to increase information reliability, increasing the maturity of the company's maintenance function and contributing to various operational and financial aspects.

The knowledge of the specialists combined with the use of process information promotes the joining of qualitative and quantitative metrics, reaching the entire scope of the company. The use of tools and methods to better structure this information assists in the success of RCM program, supporting the different decisions to be taken at each stage of the development of the methodology. In this direction, this research proposes a customized framework for the provision of qualitative and quantitative data applicable in a Smart RCM. Figure 1 presents the research scope and the dimensions involved.

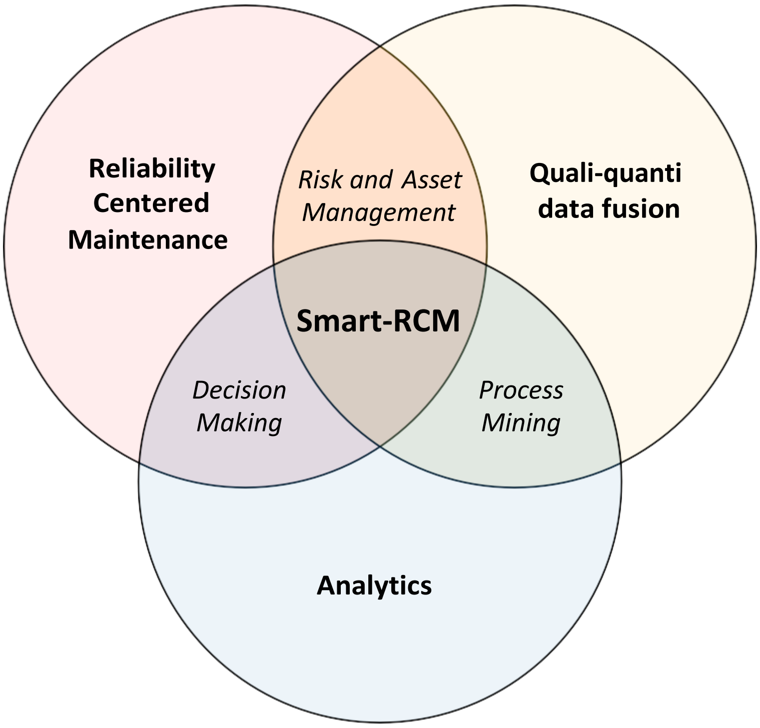


Figure 1. General research scope

In this information context, the CMMS (Computerized Maintenance Management Systems) manage the life cycle of the maintenance work-orders in accordance with selected maintenance policy (it contains knowledge about maintenance actions, past and planned, degradation models, limit threshold) [11]. However, measurement metrics are not adapted to real needs, which have a strong human factor; nor is there a roadmap of the amount of data to be collected, their processing or how they are used in decision-making [12].

Thus, the goal of this study is to create a conceptual framework, to address and process qualitative and quantitative information to a single database under measurements aspects, in order to support the decision dimensions of Smart RCM. This base should be explored in search of consistent patterns, detecting systematic relationships between variables through the application of process mining techniques. With the identification of trends in the maintenance actions, it is possible to discover hidden patterns and relationships that will support in the maintenance decisions making, making it the most productive companies, increasing quality and reducing costs.

The rule of maintenance in modern manufacturing systems is becoming more important with companies that adopt maintenance as an element of profit for business [13]. Systems are operating more efficiently, effectively and economically to sustain their long-term survival [14]. Within this context, RCM seeks to direct maintenance efforts to components and systems where reliability is paramount. The main objective is to guarantee the performance, security and preservation of the environment at a better cost-benefit level [14,15].

Qualitative information from process and maintenance sources based on the experience of specialists is not always treated in a way that is reliable for the application of RCM. The dynamism of industrial facilities, under human, technological and organizational issues, makes it difficult to maintain RCM programs. Even with a well-established audit plan, the information that is used is being updated all the time, especially the quantitative ones, that come from the process itself. Issues involving operational, environmental and safety aspects often undergo unexpected changes, changing their indicators dynamically.

1.1 PROBLEM STATEMENT

In the industry value chain, maintenance plays a key role in maintaining productive availability and enabling the use of assets throughout their life cycle at the lowest operating cost. In this context, this research brings new concepts to the RCM methodology, culminating in a modern approach conceptualized by "Smart-RCM". The originality and complexity of the research are characterized in several aspects, listed below.

- The proposed Smart-RCM model presents solutions that can be modeled with the company's vision through top-down approach (strategic, tactical and operational).
- The mapping of indicators used in RCM approaches in the literature gives the system a strong initial basis for applying the methodology. However, the system demonstrates flexibility, allowing the insertion of any qualitative or quantitative indicator, even those specific to the business process in question, ensuring the use of the most important metrics to achieve maintenance goals, focusing on reliability and availability.

- To maintain aligned and structured equipment and processes for Industry 4.0, Smart-RCM develops a consistent database that portrays the reality of the installed base in a structured, standardized manner and with a maintenance strategy appropriate to a Maintenance Management Program.
- The collection and structuring of qualitative and quantitative data provides robustness to information from maintenance information systems and processes, and from the experience of experts and analysts involved in maintenance, operation, safety and environmental processes, classic aspects of RCM approaches. These aspects support the creation of a database, to feed the Decision-Making Database (DMD), which will store and provide the data to RCM program.
- The focus is on the proposed phases for the implementation and maintenance of the program, with the strategic selection of the systems to be analyzed, complex analysis of the criticality of the most significant maintenance items, definition or review of the maintenance strategies with contemporary approach, highlighting the 4th. maintenance, enabling greater transparency in the leveling and utilization of its resources and asset management.
- The combination of classic RCM standards and publications with contemporary approaches, such as ISO 55000 (Asset Management) [10], supports the need to update the methodology, one of the shortcomings of the new generation of maintenance.
- The proposed methodology has the aid of consolidated analytical tools, which support the standardized structuring of the systems information and consumes it through multicriteria decision making methods.
- Management tools support the structuring of decision-making models, optimizing the way decision structures are built, improving the vision and purpose of metrics for company goals, highlighting strategic, tactical and operational aspects.
- Process Mining emerges as a powerful tool for discovering behaviors in systems, machines or equipment, helping to extract information and generate knowledge.
- Decision making is present in the daily routine of maintenance, which deals with complex and competitive environments. Thus, the need for quick and accurate

decisions becomes even greater. Within the scope of Smart-RCM multicriteria decision methods are well explored and used for a better structuring of problems involving decision making, based on a series of data, either quantitative or qualitative.

Maintaining Maintenance Management to better control costs and minimize unplanned downtime is a challenge for companies today, and the Smart-RCM methodology will support implementation at all stages, from selecting the most critical systems to the consolidation of an updated and adequate maintenance policy, in a structured and dynamic manner.

1.2 RESEARCH OBJECTIVES

1.2.1 General objective

Design, implementation and assessment of a Smart RCM framework, focusing on dynamic decision making, fusioning qualitative and quantitative data in advanced models of MCDMs, to increase the reliability of information and responses in the implantation and evaluation phases of methodology.

1.2.2 Specific objectives

- Conduct a general literature review on RCM approaches and criticality and fault analysis, as well as researches about multi-criteria decision-making methods, process mining and information in RCM and Industry 4.0 context;
- Map and feature qualitative and quantitative indicators currently used in RCM approaches;
- Develop a dynamic framework for RCM methodology with focus on reconciling and treatment of knowledge and use in multi-criteria decision-making processes;
- Deploy Smart RCM in a simulated process, performing the steps of the methodology to evaluate the proposed methods and tools.

- Analyze the results under aspects of optimization in decision making and improvements in maintenance strategies in the Smart RCM scenario.

1.3 RESEARCH DESIGN

In order to better present the contributions and structure of this research under methodological aspects, DSRM (Design Science Research Methodology) is used. In this context, [16] present a general methodological guideline for effective research on DSRM, that incorporates principles, practices, and procedures required to carry out such research. It is of importance in a discipline oriented to the creation of successful artifacts (may include constructs, models, methods, and instantiations), as a solution to a research problem through complex research. It includes six steps: (i) problem identification and motivation, (ii) definition of the objectives for a solution, (iii) design and development, (iv) demonstration, (v) evaluation, and (vi) communication.
Figure 2 shows the domain of the DSR methodology for this thesis. It also relates the elements to the chapters of this document, which are described below.

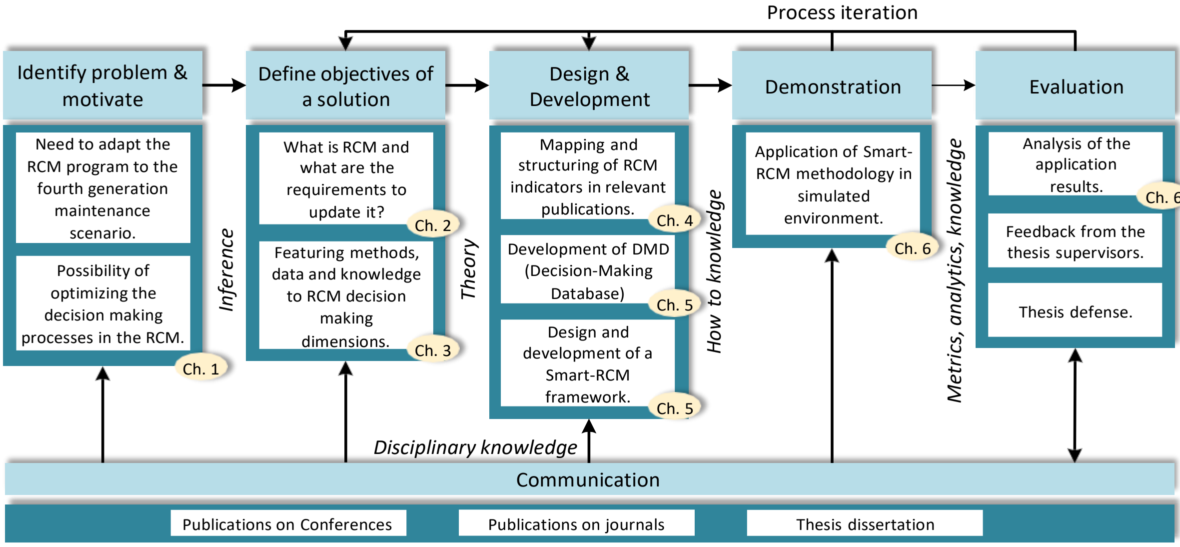


Figure 2. Research methodology instantiated to this thesis. Adapted from [16].

Chapter 1 already presented gives an introduction to the research, with an overview of the project, including methodological aspects. Topics involving the RCM methodology are presented in Chapter 2, mapping conceptual aspects, failure analyzes and maintenance strategies. Chapter 3 introduces methods used in decision-making processes whose inputs are information and knowledge presented and discussed initially in Chapter 4. This presents a mapping of indicators used in RCM processes through a systematic review, output) is the basis of the Smart RCM data fusion model presented in Chapter 5. Chapter 6 presents an application of Smart RCM in a simulated process, discussing preliminary results. Chapter 7 shows the initial conclusions of the project, emphasizing the future work of the research. Figure 2 presents the structure of the document, with all the topics involved in this research project.

1.4 RESEARCH METHODOLOGY

The present work comprises 5 steps that begin with the design of the project until its validation through the application of a practical experimentation. Figure 3 presents the steps through the IDEF0 (Integration Definition for Function Modeling), which is a technique used to model decisions, actions and activities of an organization. Using this diagram, it is easy to read the methodology and the processes that involve the present research project, helping the understanding among those involved in its development. The 5 steps (A0-A4) are explained below.

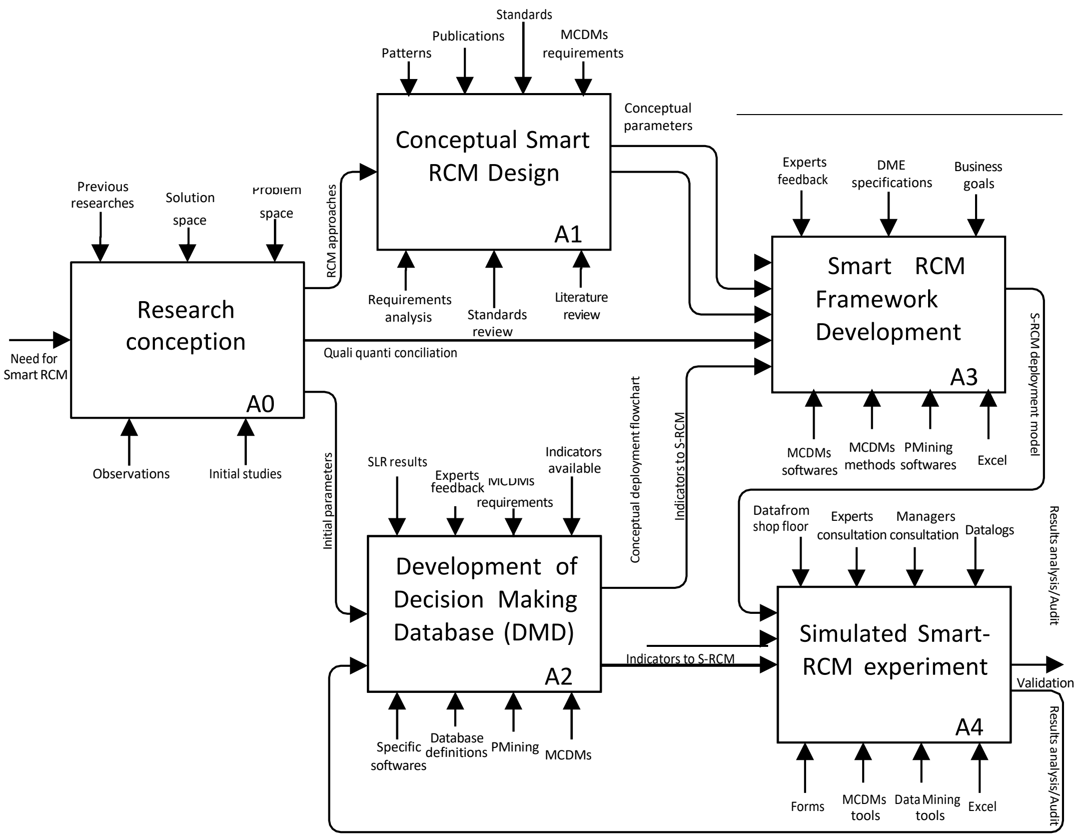


Figure 3. IDEF0 diagram from research methodology

A0 - Research conception

Through the initial analysis of Problem Space and Solution Space, observations are made in research already presented around RCM and the tools and methods used are studied. The classic RCM approaches serve as a basis for the conceptual implementation model.

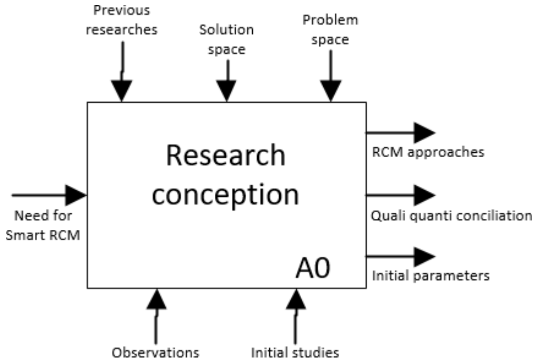


Figure 4. Phase A0 from research methodology

The need to conciliate qualitative and quantitative information is observed, generating the possibility of the proposal of a smart model, focusing on the decision making. The initial research phase generates an overview of the scope of the research, highlighting gaps among the elements involved, generating parameters and references for the construction of the project.

A1 – Conceptual Smart-RCM Design

In this phase a review is performed, under the themes that involve the project. Publications involving RCM and decision making are analyzed, with formats of scientific research projects, standards, norms and technical articles. Also, the requirements for the implementation of RCM are raised, crossing the information with the possibilities of using MCDMs tools.

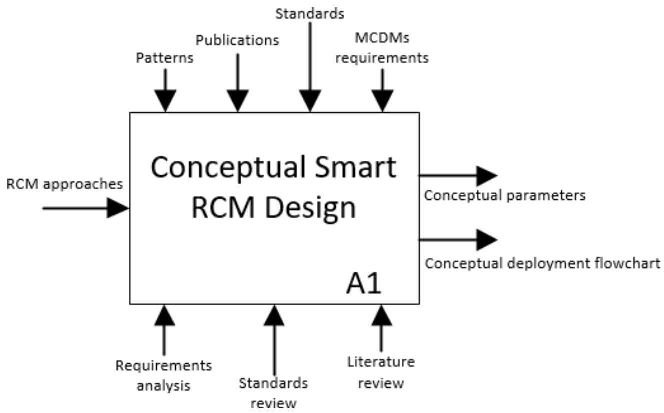


Figure 5. Phase A1 from research methodology

The outputs of this phase are: (i) a flowchart with the conceptual model for implementation and evaluation of the RCM and (ii) conceptual parameters for the general Smart-RCM framework and for future application in a simulated experiment.

A2 – Development of Decision Making Database (DMD)

This phase creates the basis of indicators used in RCM to support decision making processes. Thus, systematic review is proposed to verify the "state of the art" of RCM, focusing on information of indicators / metrics in the process of implementation of the methodology.

The database is available in the DMD (Decision-making Database), with the fusion of qualitative and quantitative indicators and periodic updates. With exits are presented the classified and characterized indicators, to select the best opportunity of its use in the decision processes.

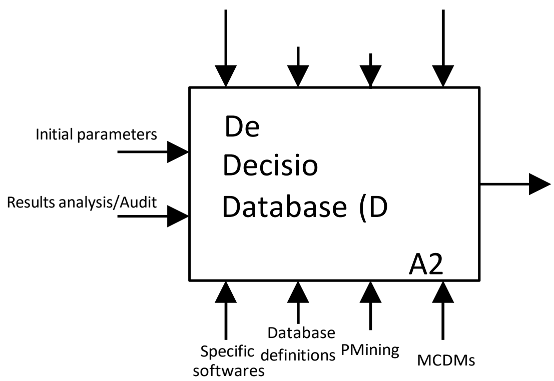


Figure 6. Phase A2 from research methodology

A3 – Smart RCM Framework development

An adapted, customized and simplified model is presented for the methodological structuring of the proposed Smart RCM model. The steps are operationalized in the framework through the MCDM models. This phase receives the information made available in the DMD as input for decision-making.

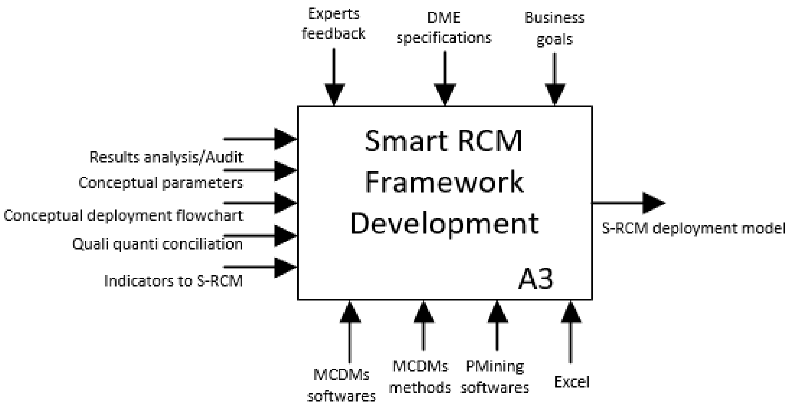


Figure 7. Phase A3 from research methodology

The inputs of this phase consist of conceptual parameters, as well as a customized RCM application model and a range of indicators extracted from contemporary RCM applied research. Furthermore, the outputs of phase A2 are used as inputs in the decision models of the RCM stages. Utilizing process information, company goals and expert experience, decision models are executed, supported by process mining (quantitative data), MCDM methods and specific software.

The dynamics of the systems involved characterize Smart RCM terminology for the present project. As a result of this phase the framework has been finalized, but with feedback after specific audit analysis.

A4 – Simulated Smart-RCM experiment

With the Smart RCM ready to be deployed, a practical experiment is proposed for validation of further discussion of evaluations. Using the information available on DMD as well as expert consultation, the model is implemented in a simulated environment using Process Mining techniques.

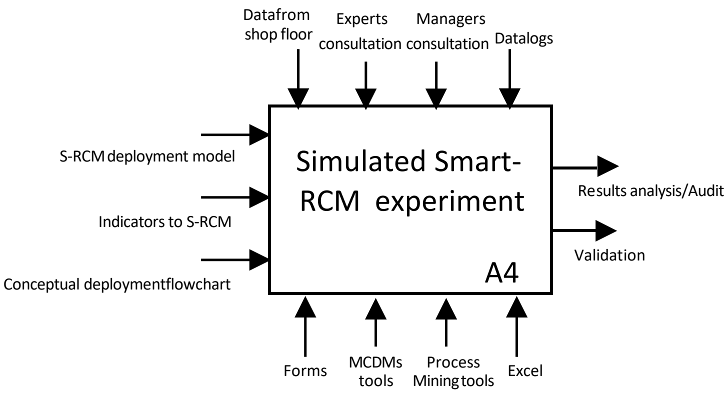


Figure 8. Phase A4 from research methodology

This phase will allow the validation of the proposed model, as well as a revision of the conceptual data collected in the previous phases of the research, allowing the continuous improvement of the program.

In order to support the design and development of this research, the following topics (2-4) present a literature review of the themes involved, according to the needs of the proposed Smart RCM model.

2 RELIABILITY CENTERED MAINTENANCE

Contemporary approaches involving reliability concepts have been widely used in business maintenance with the aim of increasing equipment availability. The intention is to keep the plant as available as possible (uptime). For this, reliability management is used to eliminate the effects of system failures caused by equipment problems and often by human factors. In its most common definition, reliability is the probability that a component will not fail to perform its function within the limits specified by the production system [15, 17-19].

In this scenario is Reliability Centered Maintenance (RCM) which consists of a methodology capable of determining the most effective maintenance strategy, reducing maintenance activities and related costs without affecting performance plan, product quality, safety or environmental integrity [9]. Initially oriented to the aeronautical industry, its objective is to direct maintenance efforts to components and systems where reliability is paramount, ensuring performance, safety and environmental preservation at a better cost-benefit ratio [14,15].

In the historical context, the aeronautics industry was the forerunner in reliability research and the effects of maintenance failures in order to meet the requirements of the FAA (Federal Aviation Agency), which was concerned about the high failure rate of aircraft engines of the time. In the late 1960s, the Air Transport Association of America (ATA) created the Maintenance Steering Group (MSG), a task force for reviewing the application of existing maintenance methods and techniques for aircraft maintenance [20].

In the early 1970s, Nowlan and Heap [21], reporting to ATA, published the MSG-1 and MSG-2 standards presenting a new form of approach to aircraft maintenance, focused on the impact of unreliable operation and safety, a methodology that became known with Reliability-Centered Maintenance [22].

The 1980 MSG-3 included the previous standards, and a joint overview of the entire aircraft industry process, being adopted as a mandatory maintenance methodology for new aircraft by the US Department of Defense - DoD, which is currently used after its last revision in 2002 [15].

The industrial needs of the 1980s led to the application of RCM in other sectors of industry, especially mining and manufacturing [20]. This spread of RCM has led to the emergence of slightly different versions of MSG-3, such as RCM II proposed by Moubray [15], the Abbreviated Classical RCM, and Smith-Hinchcliffe's [23] Experience-Centered Maintenance (ECM).

To meet the implementation of these RCM steps in a contemporary approach and in an industrial environment, the criteria that an RCM process must meet is basically defined by standards and technical publications, such as: (i) IEC 60300-3-11 [24]; (ii) SAE-JA1011 [25]; (iii) SAE-JA1012 [19,26]; Moubray (RCM II) [15] among others. The evolution of RCM patterns is shown in Figure 9 [27].

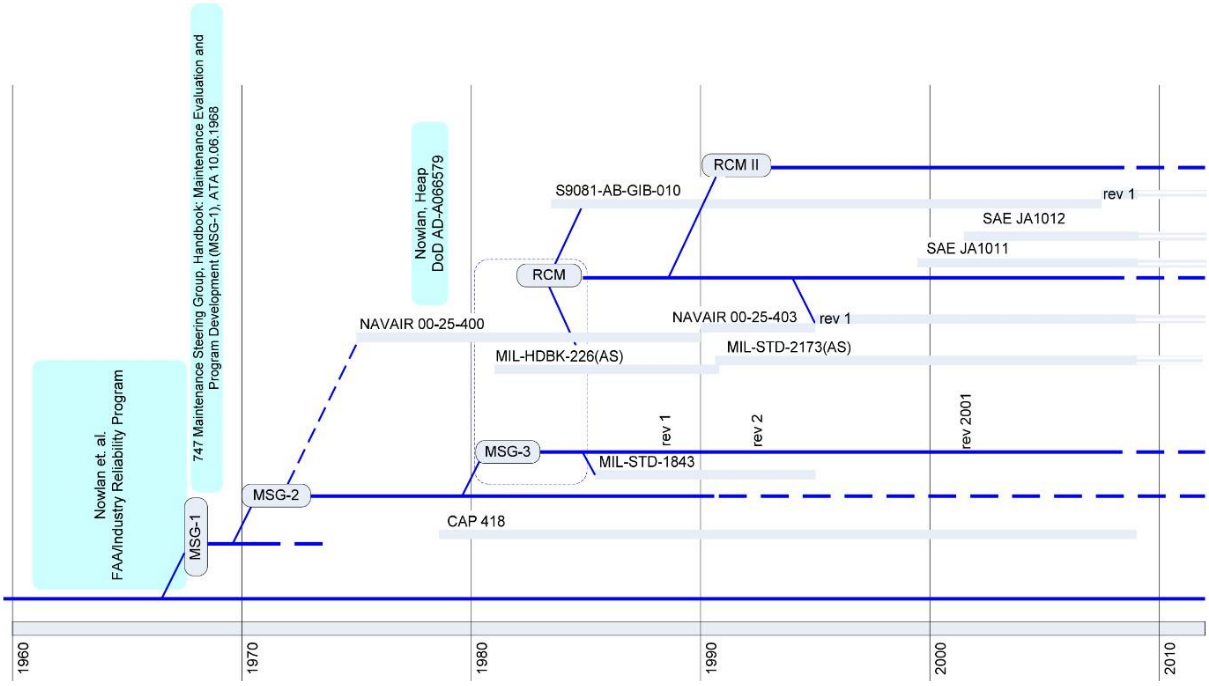


Figure 9: RCM's timeline [27]

[28] states that the outcome of an RCM program is related to the objectives of its implementation, the resources (time, physical and technical work) applied and the organization's commitment during its implementation. [20] justifies that, in order to achieve a maximum RCM result, there must be mutual support among those responsible for system design, operation and maintenance, and once the program is implemented, it must be updated periodically to include new information and possible changes. RCM also adds intangible benefits, which are often overlooked as having a negligible financial impact [20].

The literature presents different versions for the application of RCM. These versions may vary in the number of steps, deployment order, and tools used, driven by the need for the process or the author / analyst experience. However, in essence, they have a similar approach and goals. Briefly, the RCM flow can be summarized in three steps (Figure 10):

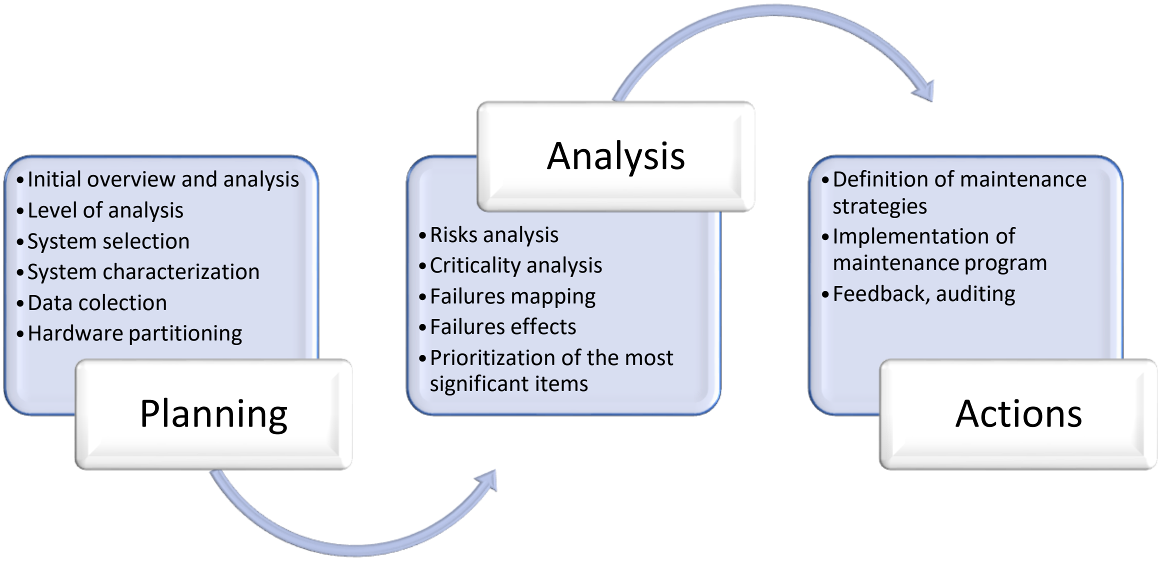


Figure 10. RCM development flow

The first step consists of an initial planning. The methodology is honorable, being necessary to delimit its application. This step results in the selection of the system to be analyzed, its hierarchical structure of equipment and the level of analysis to be performed in relation to items (machine, equipment and component). Items are analyzed in the next step by applying failure analysis methods. In this analysis, information is collected on the basis of the items, their failures and the effects of the failures and their criticism in operational, safety and environmental aspects. As a result, we obtain a criticality rating of the items, which will be reviewed later in the third step, to select the appropriate maintenance plan. The more critical the item, the more specialized its maintenance policy should be. The cycle is closed with results analysis and program feedback if necessary.

Research on the use of RCM in industrial systems is commonly found in the literature since its inception, with the aim of increasing system reliability. Over time, a number of advanced techniques have been added to the program standards, creating RCM extensions to suit your program requirements. Increasing the quantity and quality of asset information has driven this advance in research, which has helped decision-making processes.

Asset reliability is determined from the RCM design phase. Deficiencies can be detected in the design, installation, commissioning and operation phases due to human errors in decision making, leading to consequences. Skills and behavioral factors can affect equipment performance and the production process [29]. Asset reliability depends on the reliability of people, production processes and equipment. Qualitative information is incorporated into all maintenance management. Quantitative information is generated largely by systems and processes.

Recent research [30] conducts a SWOT analysis (Strengths, Weaknesses, Opportunities, and Threats) of RCM structures between 1978 and 2014. Performed by professionals or consultants, RCM models have often been used for analysis methods. of reliability with a qualitative nature. The research points out the main activities of the RCM, and its elements are identified, presented and analyzed. The results show difficulties in the RCM development due to the quantity and quality of the maintenance information. Qualitative tools such as FMEA (Failure Modes and Effects Analysis), FFA (Functional Failure Analysis), decision diagrams, among others, are widely used in RCM implementation. These studies bring together the human factor, which makes it difficult to generate a solid and reliable knowledge base for asset maintenance to be used in decision making. Quantitative approaches are related, such as analysis of the relationship between system reliability and maintenance effort, logical and structured reliability analysis, failure rate modeling, economic analysis of maintenance tasks, and the use of standard components for reliability analysis.

[23] point out the following considerations about the RCM methodology:

(i) the RCM process is not perfect, and may require periodic adjustments to baseline results;
(ii) the system or plant may undergo changes, such as design changes, equipment inclusion, technical or operational changes, which infer from the result of the analysis;
(iii) the knowledge acquired during the analysis and implementation process may be useful in revalidating the results.

2.1 FAILURE ANALYSIS

The prevention or elimination of failures is one of the basic objectives of maintenance. Component failures have the potential to overthrow RCMs first goal of "preserving system function" [23].

Once the system functions are defined, this second stage of the deployment tries to determine how the system can stop performing this function, determining actions to prevent, reduce or detect the beginning of the function loss.

[23] highlight two key points at this stage of the process: (i) the focus of the analysis is on loss of function and not loss of equipment and (ii) failures are more than just a single and simple statement of loss of a function, since most functions have two or more loss conditions, where not all are equally important.

2.1.1 Failure Classification

Failure can be defined as the interruption or alteration in the capacity of an item to perform its required or expected function, classifying it on aspects such as: origin, extension, speed, manifestation, criticality and age [15].

In RCM, faults are classified by their effect on the function of the system, being functional or potential.

Functional failure the inability of any physical item to perform a function with a pattern of performance desired by the user, being differentiated into [17]:

- Obvious failures: when detected during normal team work;
- Hidden failures: a failure not detected by the team during normal work;
- Multiple failures: When a hidden fault combined with a second fault becomes evident.

Potential failure presents with an identifiable and measurable condition of the imminence of a functional failure or its process of occurrence [15]. This concept is possible because many failures do not occur suddenly, but evolve over a period of time.

The onset of a potential failure is established when the system begins to show a change in the performance of its function, and may evolve into a functional failure. Figure 11 shows this relationship [31].

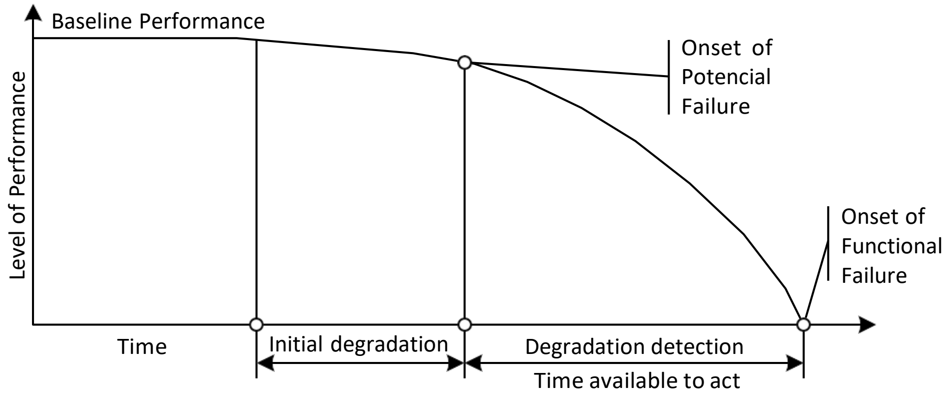


Figure 11. P-F curve [31]

The interval between the initiation of the potential failure and the occurrence of functional failure is determined "P-F range". The maintenance actions under condition must occur within this period, however their interval must be smaller than the P-F interval, detecting the potential failure before its development in functional failure [31].

2.1.2 Failure Modes

The standard SAE -J1739 [32] define failure mode as "the way a fault occurs in an item" and "the way a fault is observed in a subsystem function or component". While failure is associated with the system function, the failure mode is associated with the event that causes the transition to the failure state.

Identifying all modes of system failure allows predicting what happens when it occurs, assessing its impact and deciding what can be done to anticipate, prevent, detect, correct or even eliminate it [14].

2.1.3 Causes of failures

Generally, a failure mode can have different causes, characteristic of its manufacturing technology and its mode of operation, capable of generating own and specific failure modes. The cause of a failure may be associated with [33]: (i) project failures; (ii) defects in material; (iii) component manufacturing process; (iv) installation failures; (v) unforeseen operating conditions; and (vi) maintenance or operational failures.

All causes must be identified, including those of human origin, and that in the identification process, individuals with a total understanding of the equipment, especially from the point of view of maintenance and projects, should be involved, defining actions to avoid failures or eliminate them through their causes [33].

Due to the different phenomena that can induce a failure, the failure modes can be classified by their impact on the level of performance of the function performed [14]: (i) capacity below the desired performance; (ii) desired performance above initial capacity; and (iii) failed to perform from the outset.

2.2 FMECA – FAILURE MODE, EFFECTS AND CRITICALITY ANALYSIS

The documentation and analysis of the failures in the RCM methodology can be performed by the tools: (i) Failure Mode and Effects Analysis (FMEA); and (ii) Failure Mode, Effects and Criticality Analysis [33]. They consist of a sequence of logical steps, starting with the analysis of lower level elements (subsystems or components), identifying the potential failure modes and failure mechanisms, tracing the effect of this failure in the various levels of the system.

2.2.1 FMEA Analysis

FMEA as a systematic approach focusing on the prevention of system, design and / or process failures through an approach of identification, frequency and impact of failure modes on them [34]. The FMEA procedure is a sequence of logical steps, starting with the analysis of lower level elements (subsystems or components), identifying potential failure modes and failure mechanisms, tracing the effect of this failure at the various levels of the system [35].

The analysis of the processes can be performed in a bottom-up, when initiated by identifying the failure modes at the lowest level of the system, tracing their effects at higher levels, until reaching the highest level. Another way to perform the analysis is called top-down with an analysis of the functional and potential failures that affect the final system, identifying the causes of these failures at the lower levels of the system [36].

The analysis of the FMEA can be classified into two levels [32], which are similar in the conduction of their steps and analyzes, being different in their application focus:

- Project or Product FMEA: carried out after the project design, identifying each component of the system and the associated possible failure modes, as well as their effects on the system in question and on the product as a whole.
- Process FMEA: analysis of manufacturing systems that can infer about the quality and reliability of the product, identifying the modes of process failures and their effects on the product.

2.2.2 FMECA analysis

The FMECA is composed of two separate analyzes, the FMEA and a Criticality Analysis (CA). The FMEA analyzes different failure modes and their effects while the CA prioritizes its level of importance based on the rate and severity of the failure effect.

The results of the FMEA analysis make it possible to know and understand the weaknesses of a system (failure modes) [31], acting as a source of information in the creation of a reliability model and in the decision-making process to be taken to avoid and eliminate these failure modes.

Developed by the US Department of Defense in the 1970s as a reliability tool, FMECA was tested in a wide range of industrial applications, resulting in modified versions of the methodology, according to the application segment, MIL-1629-A (Department of SAE-J1739) and SAE-ARP5580 (automotive industry) and IEC-60812 and STUK-YTO-TR190 (electronics industry). Although each of the standards presents different versions, the main concepts and procedures are similar, however a detailed procedure must be performed for each specific application [37,38].

2.2.3 FMECA application flow

The different versions of the FMECA have a similar application flow between them, where for the FMECA analysis, the first step is the realization of an FMEA, used as a database for Criticality Analysis (CA). Figure 12 [39] shows the application flow for an FMECA according to the IEC 60518 standard.

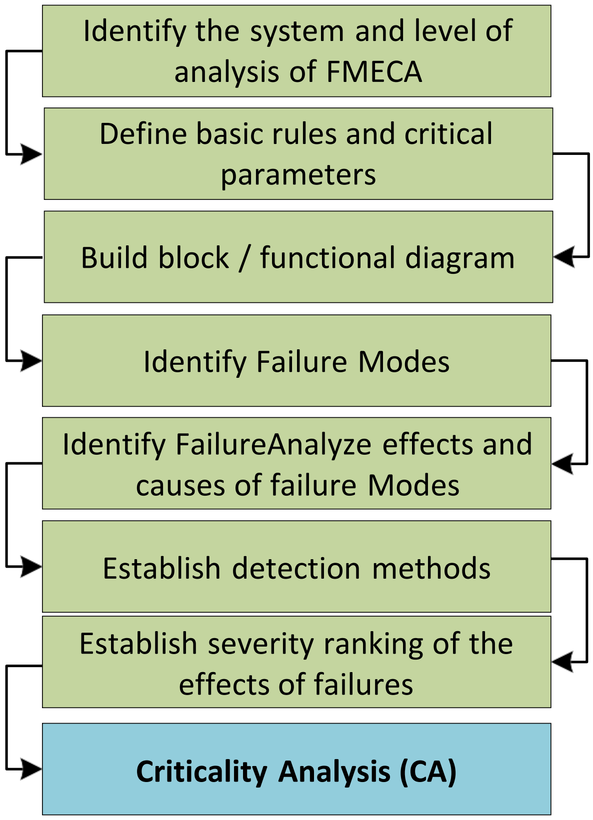


Figure 12. FMECA Application Flow [39]

The FMECA consists on a collection of information, document creation and reporting. This information should be documented in a spreadsheet that will ensure the documentation of failure modes associated with each functional failure, its causes and effects, also assisting the analysis of RCM maintenance actions [38].

2.3 MAINTENANCE STRATEGIES

Traditionally, maintenance classification is performed according to the planning of the activities and according to the objectives of the maintenance method applied. With regard to planning, maintenance might be carried out in a planned manner, executed under a pre-established time and conditions, or in an unplanned manner, as the need arises.

Maintenance methods or policies express the way in which the intervention is performed in the equipment [13] and the difference between these methods is at the moment the maintenance activity is carried out [35].

In this context, RCM plays an important role at strategic and tactical levels and helps design and define maintenance plans that ensure desired equipment reliability [7].

Basically, maintenance tasks can be summarized into two types: (i) Corrective Maintenance and (ii) Preventive Maintenance [24]. Corrective Maintenance is also called Reactive Maintenance, or RtF (Run-to-Failure). Preventive Maintenance is usually subdivided into TBM (Time Based Maintenance) and CBM (Condition Based Maintenance). Figure 13 [24] presents a sample of maintenance classification, with types of maintenance tasks, in a classical approach.

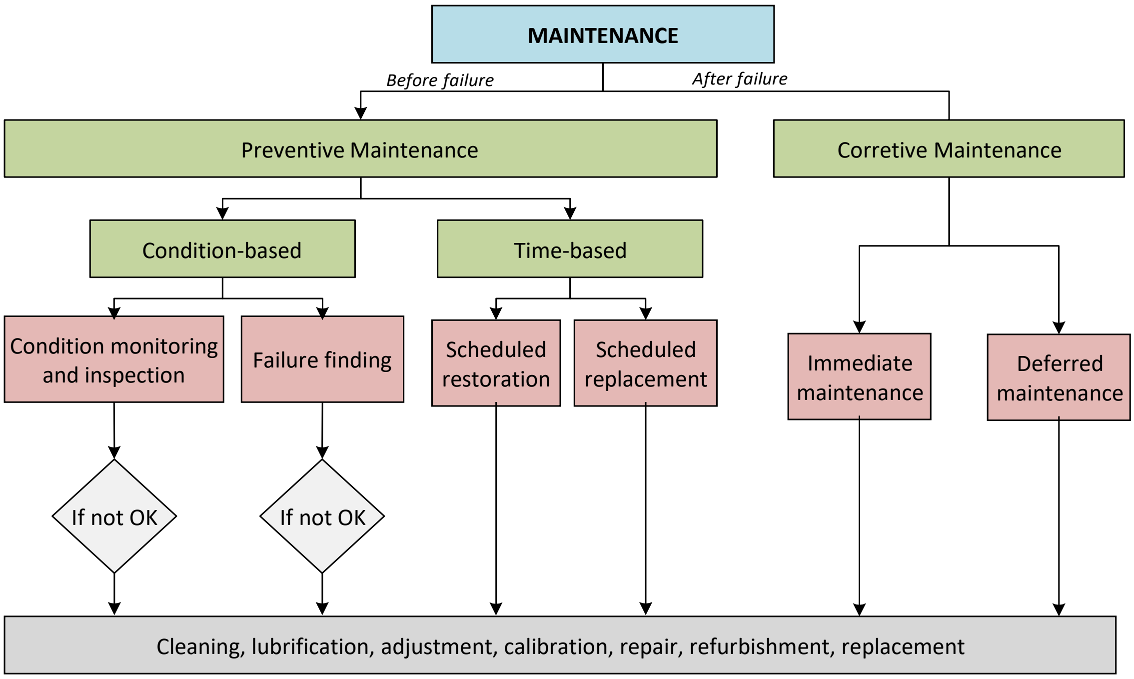


Figure 13. Types of maintenance tasks [24]

Modern manufacturing concepts bring new approaches to maintenance strategy. In this scenario emerges Prescriptive Maintenance, the most modern and advanced of strategies, considered the next step after preventive and predictive maintenance for proactive and intelligent maintenance planning [40]. Figure 14 presents a modern roadmap for classification of maintenance policies. [Adapted from 41].

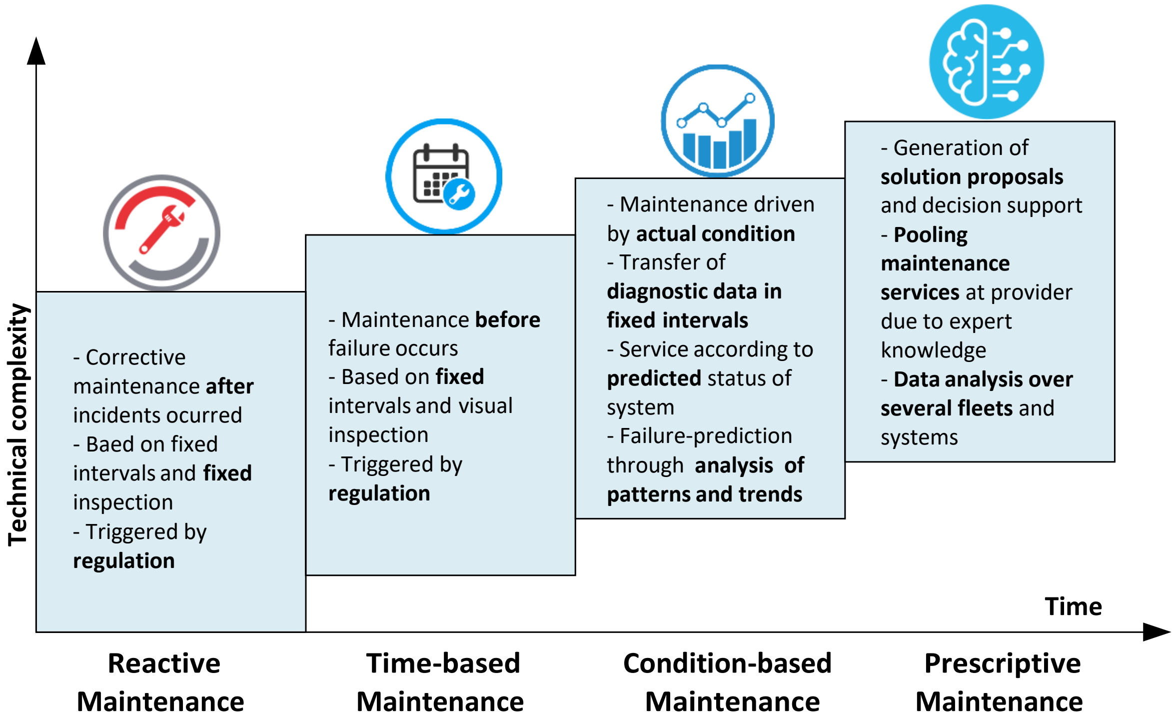


Figure 14. Roadmap to prescriptive maintenance. Adapted from [41]

This approach defines 4 maintenance strategies: (i) Reactive Maintenance, (ii) Time-based Maintenance, (iii) Condition-based Maintenance and (iv) Prescriptive Maintenance. Each strategy is best presented in the following topics.

2.4.1 RM - Reactive Maintenance

The unscheduled maintenance or repair to return assets to a defined state, performed by maintenance personnel or professionals who have realized these deficiencies or failures [13]. Reactive maintenance restores the functions of an item after failure has occurred or performance fails to meet stated limits. Some failures are acceptable if the consequences of failure (such as production loss, safety, environmental impact, failure cost) are tolerable compared to the cost of preventive maintenance and the subsequent loss due to failure. This results in a planned run-to-failure approach to maintenance [24].

2.4.2 TbM - Time-based Maintenance

All tasks performed in a specific, planned and periodic schedule to maintain an asset in defined working conditions through the process of analysis and reconditioning [13]. Time-based Maintenance can also be predetermined, based on a fixed interval (such as calendar time, operating hours, number of cycles) consisting of scheduled refurbishment or replacement of an item or its components [24].

2.4.3 CbM – Condition-based Maintenance

Use of modern methods of signal measurement and processing to accurately predict and provide diagnostics of asset conditions during operation [13]. It has become possible using smart, connected technologies that unite digital and physical assets. Is normally scheduled or based on a predetermined set of conditions while corrective maintenance is unscheduled. It is not unusual to defer reactive maintenance for a later convenient time when redundancy preserves function [24].

2.4.4 PRx – Prescriptive Maintenance

With industry digitization and the advancement of computing and automation technologies, a new era is emerging in maintenance, called Prescriptive Maintenance (PRx). Its concept goes beyond fault prediction. Based on analyzes of historical data and data received in real time, maintenance decision making is predicted by a system and a course of action is prescribed [40].

PRx is a component of the Industrial Internet of Things (IIoT). It utilizes machine learning and automated data review to prevent machine, equipment or device failures. Industry experts call this preventive maintenance with integrated intelligence [42].

Prescriptive Maintenance aims to provide a decision on which maintenance to perform at what time. It uses historical data and real-time information to provide a maintenance decision as an output. This decision can be used to support human decision making for maintenance planning or in a fully automated maintenance planning system, enabling intelligent maintenance planning to prevent failures and increasing machine efficiency, availability and reliability [40].

Companies must interpret and consume data before it expires. Enterprises are missing out on valuable insights, with many disconnected sources generating and collecting data on their own, contributing only parts of the overall picture rather than providing a broad view [42].

Recent research [43] predicts that prescriptive maintenance in 2030 complements the prediction of disturbances and failures, also suggesting the most appropriate counteraction. The economic impact will be substantial as fact-based planning increases availability, extends equipment life, and enables more economical maintenance with fewer resources. The key challenge will be to incorporate predictive and prescriptive data analytics into easy-to-use decision support systems. Based on reactive, time-based, condition-based and prescriptive maintenance, different approaches are taken to maintenance tasks.

The literature presents other techniques and methods of maintenance, which can be classified as types of maintenance or included in the methods already described. However, the objectives and all methods are summarized in the correction, elimination and prevention of failures, whether or not they are planned.

In order to be able to make rational and justifiable tactical decisions concerning maintenance, one needs to have a clear idea of what the advantages and disadvantages of each maintenance policy are. In addition, a supporting maintenance concept is required [8].

2.4 DISCUSSIONS

The evolution of industrial information systems and maintenance has provided a rapid advance in the maintenance methods implemented in companies. The search for increased reliability also encourages developments in new tools and methodologies, such as RCM. Thus, this topic presented historical and conceptual details of RCM, which is considered the problem space of the present research.

As it is an already consolidated and flexible methodology, it is noticeable in the maintenance timeline the advances in the publications and standards available for the most diverse types of business segments. In this context, the present research advances with the insertion of a new RCM approach, bringing analyzes of risks and reliability of industrial systems in the current context, with information treatment and advanced tools for decision making.

The RCM approaches raised in the literature provide the necessary support for the adaptation of a customized, easy-to-interpret and detailed implementation model in its development process. For increased reliability and risk reduction, RCM's main focuses, fault analysis is a very important point in the methodology. The objective is to perform the verification of the impacts of system failures, as well as their effects and their criticality, issues that are developed in the FMECA analysis, central point of the implementation of RCM.

According to [44] RCM has two obvious disadvantages in the current application: (i) RCM is an analysis tool based on experience and logical decision, so it lacks support from the quantitative model; (ii) for maintenance activities, RCM is generally a static maintenance method. In other words, after a review of the RCM, the maintenance strategy will be corrected without considering other operating conditions of the equipment.

Traditional RCM approaches need to be improved by considering changes in equipment health status and making more accurate maintenance decisions based on quantitative analysis. With an in-depth analysis of the strengths of the methodology and confronting the shortcomings pointed out by [144], this research represents an approach called Smart RCM, with a modern focus, with an emphasis on: (i) fusion of qualitative and quantitative data to create a database for be consumed by the RCM program steps; (ii) use of quantitative data analysis and processing techniques (indicators); (iii) use of modern tools to consume the database built in decision making in the RCM stages; (iv) a risk based methodology and alignment with contemporary aspects emerging in the fourth generation of maintenance (maintenance analytics); (v) use of management tools to support strategic decisions; (vi) use of publications and standards consistent with each proposed step; and (vii) presentation of a dynamic general framework to adapt the methodology to modern approach, focusing on asset management. The result is a more holistic, integrated, and rigorous way to develop asset treatment and risk mitigation strategies for physical assets.

Through a well presented analysis and with reliability in the data and information used the choice of the maintenance strategies are better carried out, providing improvements in the availability of the assets.

For a better understanding of the scope of Smart RCM proposed by this research, chapter 3 presents the methods and tools used for decision making in the

RCM program. It also introduces concepts about data, information and knowledge inserted in RCM deployment and evaluation environment, emphasizing the importance of updating the methodology with modern concepts and tools. Data structuring supported by process mining techniques support the context of prescriptive analysis, a modern concept with application space for industrial maintenance.

3 METHODS, DATA AND KNOWLEDGE TO DECISION-MAKING DIMENSIONS

A decision-making is to choose one among a set of countable alternatives - usually finite - or uncountable, using two or more criteria (multi-criteria). When it is assumed that the criteria are known, the decision problem is called deterministic. When values are not known, it is called non-deterministic or stochastic [45]. Thus, several tools are employed with the aim of making these processes more agile and reliable. Figure 15 presents a decision-making process.

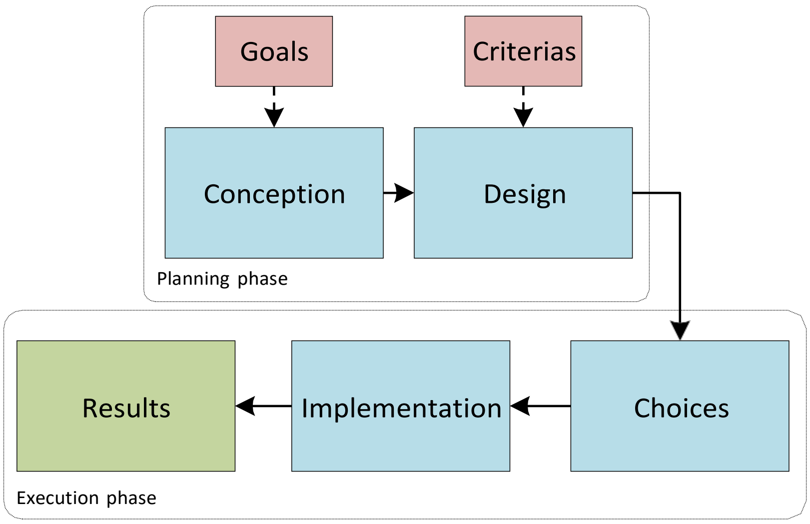


Figure 15. DMMs phases

The following topics present the elements that integrate the operationalization of a decision-making process, as well as contextualize the inputs and outputs of information in the scope of the research.

3.1 DECISION MAKING METHODS

The decision-making methods are often characterized by the presence of several conflicting criteria, which forces the decision maker to seek reasonable compromises by performing trade-offs between discordant objectives [46]. In this context, the present research proposes the use of decision-making tools to provide robustness in the decision making stages of the RCM implementation, increasing the reliability of the information and improving the quality of the selections of the available alternatives.

MCDM methods are commonly used in maintenance decision-making. These techniques allow information on maintenance goals and objectives to be converted into evaluation criteria and brought into a framework that incorporates stakeholder views. A literature review on researches with applications of MCDMs in the selection of maintenance strategies is found in [47]. It is an important intervention to address multiple and conflicting goals where decision makers value them differently. Applications of MCDM methods allow a structured and consistent evaluation, integrating quantitative and qualitative criteria [48,49].

The following sections present the decision-making methods employed in developing the proposed Smart-RCM.

3.1.1 SWOT - Strengths, Weaknesses, Opportunities and Threats

Used in the present research to support the choice of decision criteria, the SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis is a commonly used tool for analyzing external and internal environments simultaneously in order to acquire a systematic approach and support for a decision situation [50]. Generally, SWOT is a list of statements or factors with descriptions of the present and future trend of both internal and external environment; the expressions of individual factors are general and brief which describe subjective views [51].

The analysis of the factors at a strategic level helps the selection and organization of the criteria to be used in decision-making methods, since it presents an overview of the business process. Such criteria should be mapping the opportunities and challenges of the company, making it possible to choose the best alternatives in its decision making.

The SWOT analysis is commonly used at the beginning of the process (strategic planning) or for the optimization of a strategy already implemented. The leadership team should be strongly involved as they must be able to analyze the organization and provide insight into the competitive environment of possible business scenarios. It involves systematic thinking and comprehensive diagnosis of factors relating to a new product, technology, management, or planning [52]. Figure 16 shows how SWOT analysis fits into an environment scan [52].

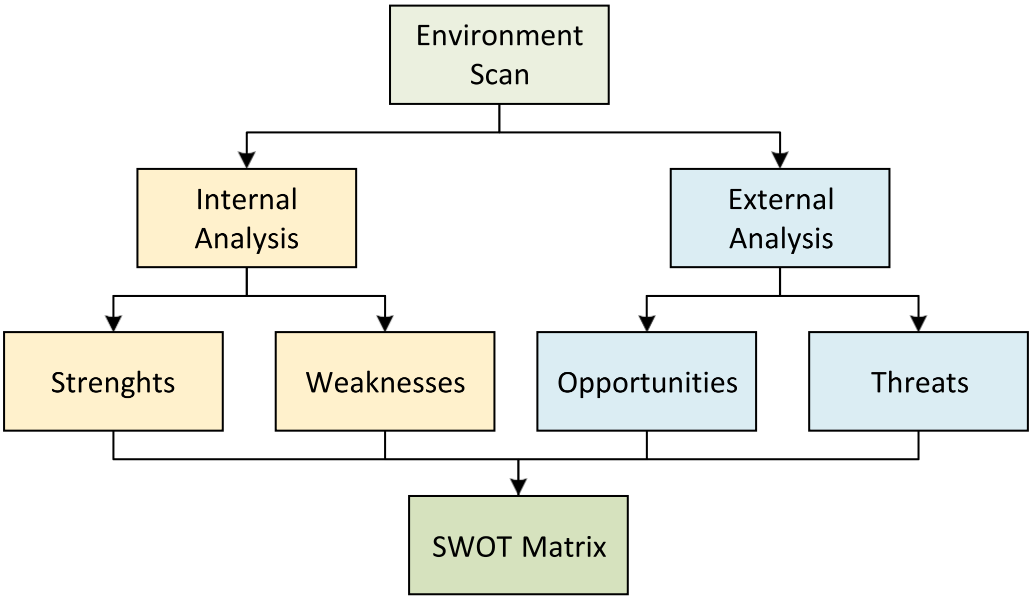


Figure 16. SWOT analysis framework [52]

SWOT analysis allows the company to act more reliably in the face of market challenges, as it gets to know its strengths, its weaknesses, how it affects the company and, mainly, what measures are necessary to achieve better results.

3.1.2 AHP - Analytic Hierarchy Process

The AHP method is one of the most classic and popular analytical techniques for analyzing complex problems in decision making. It consists of a family of procedures that use the pairwise comparison of criteria, where one asks how important one criterion is in relation to the other, being a simple, intuitive and flexible way for decision makers to analyze the problem [129].

Figure 17 presents a generic and hierarchical model of the structure of this method, where it is observed that the problem is segmented into sub problems, which can be understood and assessed subjectively more easily through objectives, attributes, criteria and alternatives.

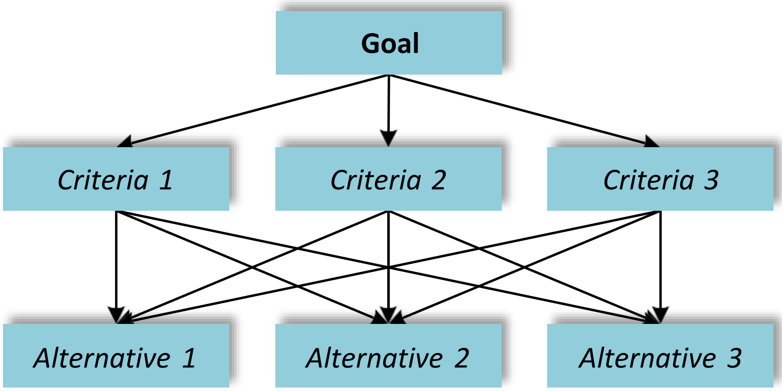


Figure 17. AHP hierarchical and generic model. Adapted from [130].

Therefore, the AHP hierarchy can contain as many levels as necessary to characterize the decision-making problem space [68]. In this method, peer-to-peer comparisons are made at the same level, that is, alternative with alternative and criterion with criterion. The scale used to make this comparison is shown in Table I, which is also known as the Saaty scale.

Table I. Fundamental scale of the AHP method: Saaty scale. Adapted from [130].

Values	**Definition**	**Explanation**
1	Equal importance	Both activities contribute equally to the objective.
3	Moderate importance	Experience and judgment slightly in favor of one activity in relation to the other.
5	Essential or strong importance	Experience and judgment considerably in favor of one activity in relation to the other.
7	Very strong importance	One activity is highly valued in relation to the other; dominance in practice.
9	Extreme importance	The highest possible level of difference between activities.
2, 4, 6 e 8	Intermediate values (if necessary)	–

The AHP methodology can be explained by the following steps [131]:

- The problem must be broken down into a hierarchy (relationship between elements at one level with another) of objective, criteria, sub-criteria and alternatives;
- Data are collected by specialists or decision makers corresponding to the hierarchical structure in order to carry out a qualitative peer-to-peer comparison based on the Saaty scale;
- The comparisons are then organized into a square matrix (the size of the matrix refers to the number of criteria, subcriteria, alternatives, etc.);

- The eigenvalues and their respective eigenvectors are normalized, giving the relative importance of the compared criteria, with the elements of the eigenvector being the weights of each comparison;
- The matrix consistency should be calculated / evaluated, and if the consistency ratio is greater than 0.1 (10%), it is suggested to reassess the answers;
- The index of each alternative is multiplied by the weight of each subcriterion and / or criterion, aiming, at the end, to obtain a global ranking of the options.

It is observed the ease of implementation of this method, which can be developed through tables and electronic spreadsheets. Therefore, the AHP method has some advantages over other methods, namely: hierarchical structuring of decision problems; determining the weights of each criterion; adaptable, easy and intuitive for teams that contain more than one decision maker; simplicity in peer-to-peer comparison; among others.

In turn, some of the negative points are: the pairwise comparison can be considered a superficial way of comparing a set of options, and if the nine-value Saaty scale is considered, this weakness is more evident; for a level of inconsistency greater than 10%, it is suggested that decision makers reevaluate their choices; there can easily be differences in responses between decision makers and, therefore, different results; the data analyzed is based only on the experience of the users; among others [132].

As already mentioned, the decision makers should assign weights on a scale of 1 to 9 for each criterion, comparing them pearly [53]. Thus, this method can only be used when the parameters are passive and have their importance measured on a quotient or ratio scale.

That is, all parameters must be comparable to each other. As an example, comparing the criteria a_1, a_2 and a_3 where $a_1 > a_2 > a_3$, i.e.:

$$a_1 = p_{12} * a_2 = x * a_2 \quad (1)$$

$$a_2 = p_{23} * a_3 = 2x * a_3 \quad (2)$$

Consequently,

$$a_1 = p_{13} * a_3 = 3x * a_3 \quad (3)$$

Where p_{ij} represents the degree of importance of criterion i in relation to criterion j. With this information the criteria priority table is set up. After this assembly, the sum of the lines is obtained obtaining the value w_{ij} and then the results obtained must be. The subsequent step is the inconsistency test, which is used to verify the existence of a deviation between the comparisons, where the zero result indicates the perfect consistency, whereas values greater than 0.1 can substantially increase the decision error. The Consistency Result (CR) is determined by equation [53]:

$$RC = \frac{\left(\frac{\mu_{max} - n}{(n-1)}\right)}{RI} \tag{4}$$

$$\mu_{max} = \frac{1}{n * \sum w_n} \tag{5}$$

Where:

μ_{max} = Index that relates the criteria of the Consistency Matrix and the weights of the Criteria;

n = Number of criteria;

RI = Index table in function of n [46].

After performing all the previous steps, the calculation of CR will be the decisive factor for the acceptance of the result obtained, causing new analysis to be done, changing variable weights or momentarily disregarding some restrictions in order to understand the logic of the result, if the values found are not satisfactory.

An example of AHP application is available in [53,119].

3.1.3 ELECTRE - Elimination and Choice Translating Algorithm

The ELECTRE method provides a systematic assessment based on the concept of prioritization / classification relationships (outranking), which allow the decision maker to express preference risk, being able to consider the intangible and non-monetary effects of the alternatives [133]. Additionally, this method is capable of dealing with discrete criteria of a quantitative and qualitative nature, providing a complete ordering of the options [134].

In this way, the process performed by the ELECTRE family to obtain the results (grouping and / or prioritizing the alternatives) is summarized in six stages [135]:

i. Define the reference actions;

ii. Determine the agreement indexes (sum of the weights of the attributes for which the alternative “a” is better than “b”) by criterion;

iii. Calculate the global agreement;

iv. Determine the rates of disagreement (absolute difference between the pair of attributes divided by the biggest difference over all pairs) by criterion;

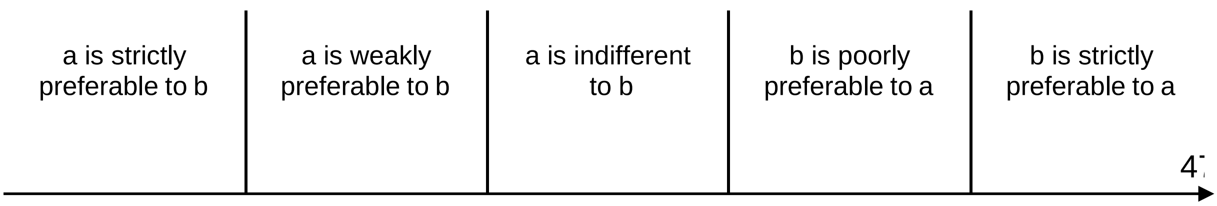
v. Obtain the degree of credibility;

vi. Determine the prioritization or grouping relationship (outranking or clustering).

According to [135], the output (result) of ELECTRE differs from other methods, in that it provides not only a global preference of the alternatives, but a partial ranking, sometimes complete, of the same ones, causing uncertainties and inaccuracies to be considered in the analysis.

In general, the advantages that the ELECTRE family provides for MCDM problems are that there is the possibility of using quali-quanti criteria, the results are validated and justified, and it is possible to work with heterogeneous scales. Regarding the disadvantages, this method is less versatile than the others and requires a good understanding of the objective, especially when dealing with quantitative characteristics [132].

In order to explain the theoretical basis of the ELECTRE method, it is first necessary to understand that there are the so-called pseudo-criteria, which are built-in adjunct checks in order to better compare the criteria [46]. The traditional classification methods start from the relation of preference and indifference to compare alternatives. For example, comparing two alternatives "A" and "B", to say that "A" exceeds "B", means that "A" is at least as good as "B". On top of the traditional methods reasoning, the ELECTRE methods introduced the concept of limits of indifference q, which signify the threshold that one alternative can transit until it is indifferent to the other. Figure 18 [46] presents the difference limit between the parameters.



aPb	aQb	aIb e bIa	bQa	bPa
g(a) - p	g(a) - q	g(a) + q	g(a) + p	g(b)

Figure 18. Situations of preference for pseudo-criteria [46]

Where:

$g(.)$ = Evaluation function;

i = Preference limit;

q = Indifference limit.

These criteria are introduced in the model to reduce inaccuracies and indeterminations in the performance of alternatives, and thus starting from the affirmation of overcoming existing between the alternatives, the ELECTRE method needs to ensure that this relationship is true and for this it is necessary to calculate the criteria of agreement and discordance [53].

$$C_{(a,b)} = \frac{K^{+}{}_{(a,b)} + K^{=}{}_{(a,b)}}{K^{+}{}_{(a,b)} + K^{=}{}_{(a,b)} + K^{-}{}_{(a,b)}} \qquad (6)$$

Where:

$K^{+}{}_{(a,b)}$ = Sum of the weights of the criteria where $g_{(a)} > g_{(b)} + q$;

$K^{=}{}_{(a,b)}$ = Sum of the weights of the criteria where $-q\ g_{(a)} - g_{(b)}\ q$;

$K^{-}{}_{(a,b)}$ = Sum of the weights of the criteria where $g_{(a)} < g_{(b)} - q$;

$C_{(a,b)}$ = Value of agreement.

The discordance calculation can be done in two ways, absolute and relative:

Absolute: when $D_{(a,b)}$ is the maximum difference between $g_{i_{(b)}}$ and $g_{i_{(a)}}$ for $g_{i_{(b)}} > g_{i_{(a)}}$, divided by the scale interval of criterion i, where i represents the criteria.

$$D_{(a,b)} = max(0, \frac{g_{i_{(b)}} - g_{i_{(a)}}}{Scale_1}, to\ i = 1, \dots n; \qquad (7)$$

Relative: relative where $D_{(a,b)}$ is the maximum value of $(g_{i_{(b)}} - g_{i_{(a)}})/g_{i_{(a)}}$, for a criterion i where $g_{i_{(b)}} > g_{i_{(a)}}$.

$$D_{(a,b)} = max(0, \frac{g_{i_{(b)}} - g_{i_{(a)}}}{g_{i_{(a)}}}, to\ i = 1, \dots n; \qquad (8)$$

ELECTRE TRI allows the allocation of a set of alternatives in predefined categories, based on the comparison of alternative a with the limits of each category, as shown in figure 19 [136].

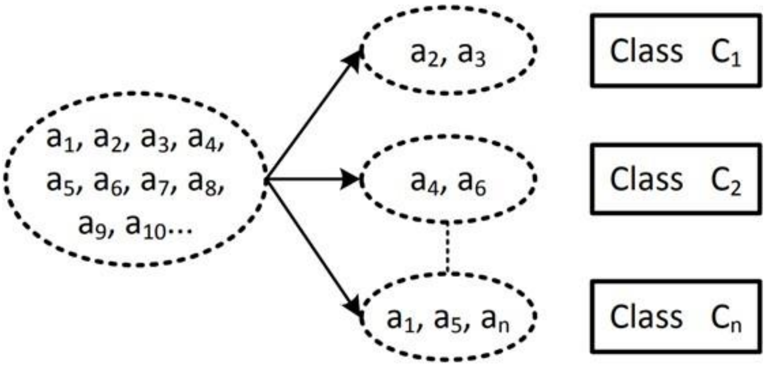


Figure 19. Modeling example of ELECTRE TRI [137]

In this method the evaluations of the alternatives for each criterion $\{g_1...., g_i ....., g_m\}$ are considered, a set of profile indices $\{b_1..., b_h ...., b_p\}$, where categories $(p+1)$ are then defined, where bh represents the upper limit of the category Ch and the lower limit of the next category C_{h+1}, $h=1, 2, ..., p$. Figure 20 illustrates the limits between categories of the method.

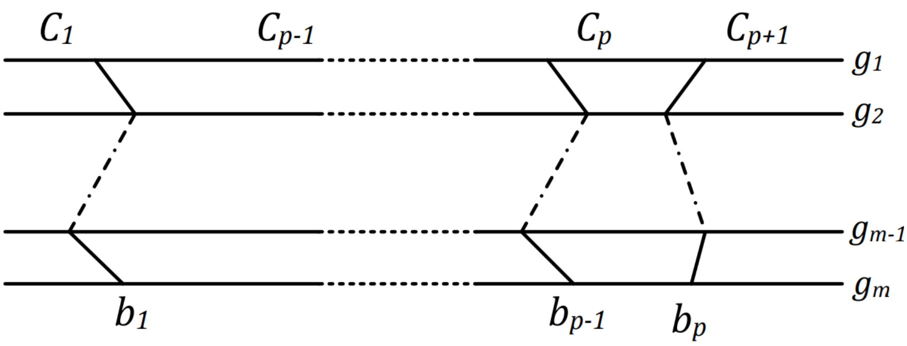


Figure 20. Limits between categories [137]

Through a pseudo-criterion, preferences are defined for each criterion (g), where the preference limits $p_j\,[g\ (b_h)]$ and indifference $q_j\,[g\ (b_h)]$ form the intra-criterion information, where $q_j\,[g\ (b_h)]$ specifies the biggest difference $(g_j\ (a)\text{-}g_j\ (b_h))$, which preserves the indifference between alternative “a” and “b_h” using the g_j and $p_j\,[g\ (b_h)]$ criterion represents the smallest difference $(g_j\ (a)\text{-}g_j\ (b_h))$, which is compatible with the preference of the alternative “a” over “b_h” for the same criterion [137]. The preference structure of the method allows for a hesitation zone, represented by a weak preference, not allowing a sudden change between a strict preference and indifference on the part of the decision maker.

Two conditions to validate statement C:

- Agreement: the overclassification aSb_h will be accepted when most criteria are in accordance with the statement;
- Non-disagreement: when the agreement condition does not exist, no criteria can oppose the aSb_h statement.

To build the overclassification relationship, ELECTRE TRI uses a set of veto thresholds ($v_1(b_h), v_2(b_h), \ldots, V_m(b_h)$), applied in the disagreement test, where ($v_j(b_h)$) represents the smallest difference between $g_j(b_h) - g_j(a)$ incompatible with the statement aSb_h. The indices of partial agreement $c_j(a, b)$, agreement $c(a, b)$ and disagreement $d_j(a, b)$ are calculated by equations 9, 10 and 11.

$$c_j(a,b) = \begin{cases} 0 \;\; if \;\; g_j(b_h) - g_j(a) \geq p_j(b_h) \\ 1 \;\; if \;\; g_j(b_h) - g_j(a) \leq q_j(b_h) \\ \dfrac{p_j(b_h) + g_j(a) - g_j(b_h)}{p_j(b_h) - g_j(b_h)} \;\; in\ other\ cases \end{cases} \quad (9)$$

$$c(a,b) = \frac{\sum_{j \in F} k_j c_j(a, b_h)}{\sum_{j \in F} k_j} \quad (10)$$

$$d_j(a,b) = \begin{cases} 0 \;\; if \;\; g_j(b_h) - g_j(a) \leq p_j(b_h) \\ 1 \;\; if \;\; g_j(b_h) - g_j(a) > v_j(b_h) \\ \dfrac{g_j(b_h) + g_j(a) - p_j(b_h)}{v_j(b_h) - p_j(b_h)} \;\; in\ other\ cases \end{cases} \quad (11)$$

[137] present the construction of a credibility index $\sigma(a, b_h)$ [0.1] that validates the statement aSb_h when its value is greater than or equal to the cutoff level (λ), with $\lambda \in [0.5,1]$.

$$\sigma(a, b_h) = c(a, b_h).\prod_{j \in \bar{F}} \frac{1-d_j(a,b_h)}{1-c_j(a,b_h)} \quad (12)$$

Where, $\bar{F} = \{j \in F: d_j(a, b_h) > c(a, b_h)\}$

After calculating the indices, a cut-off level is applied $\lambda \in [0.5.1]$, which determines the preference relationships by the condition: $p\ (a_k, b_h) \geq \lambda \rightarrow a_k S b_h$. In this way, it can be stated that the higher the value of λ, the more stringent the subordination conditions of an alternative will be, which contributes to the occurrence of incomparability between the alternatives [136]. Thus, according to [136,137] the allocation of alternatives in the categories can be carried out in two ways:

- *Pessimistic procedure*: it consists in successively comparing the alternative "a" with b_i, for $i = p, p\text{-}1, , 0, b_h$, starting in the first profile, b_p (the largest b_h), such that aSb_h, which results in the inclusion of the alternative "a" in the category $C_{h+1}(a \rightarrow C_{h+1})$.
- *Optimistic procedure*: it consists in successively comparing the alternative "a" with b_i, for $i = 1, 2, p, , b_h$, starting with the first profile, b_1 (the smallest b_h), such that "b_h" be preferable to alternative "a", with the inclusion of alternative "a" in the category C_h $(a \rightarrow C_h)$.

If b_h is the first limit value, where $a_k S b_h$, the alternative a_k is assigned to class C_{h+1}. Since b_{h-1} and b_h are the limits of class C_h, this procedure allocates a_k to the highest class C_h, so that a_k overclasses b_{h-1} $(akSb_{h-1})$. The optimistic procedure successively compares the value of a_k over b_i, $i = 1, 2, \ , p$. If b_h is the limit value so that $b_h P_{ak}$, a_k is assigned to the lowest C_h class, where the upper limit value b_h is preferred to a_k $(b_h P_{ak})$.

[53] observe that the understanding of the ELECTRE TRI algorithm requires an additional effort, since the fear in its application is based on concepts of fuzzy logic, however, they emphasize that understanding and modeling of the method does not require detailed description of the classification algorithm.

3.1.4 PROMETHEE - Preference Ranking Method for Enrichment Evaluation

Developed from ELECTRE, the PROMETHEE method was conceived with the objective of creating a simpler procedure in relation to its precursor, since the first requires many parameters that, many times, do not make sense to the decision maker [138]. Even though both techniques are vulnerable to subjectivity, especially for technical parameters, PROMETHEE demonstrates greater resistance to variations in parameters, thus showing greater solidity in the results.

PROMETHEE is a well-established and consolidated decision support system that deals with the evaluation and selection of a set of options based on various criteria, aiming to obtain a ranking among them. Thus, the great advantage of this method is its simplicity and ability to approximate the way the human mind expresses and synthesizes preferences when facing multiple contradictory decision perspectives [139], being one of the reasons why this technician can handle uncertain information, including qualitative and quantitative criteria.

The PROMETHEE family contains ramifications (versions) - I, II, III, IV, V, VI, GDSS, GAIA, TRI and CLUSTER - which have the purpose of solving ordering and application problems in systems involving fuzzy preferences [138]. These methods also use peer-to-peer comparison in order to order the alternatives in relation to the previously specified criteria, presenting ease of use and low complexity [134].

The methodology for implementing PROMETHEE is summarized by [54] in five stages, namely:

i. Determine deviations based on peer-to-peer comparisons;
ii. Choose and apply the preference function - usual, U shape (almost criterion), V shape (preference threshold), levels (pseudo criterion), displaced V shape (area of indifference) or Gaussian;
iii. Calculate the global preference index (or total);
iv. Calculate the ordering flows (partial ranking - PROMETHEE I);
v. Calculate the net (resulting) ordering flow (full ranking - PROMETHEE II);

The ordering flow mentioned in the implementation steps refers to the mathematical calculations that analyze how far one alternative outperforms (outranks) all the others (positive ordering) and how far out of that alternative (outranked) by all others (negative ordering) [138]. Visually, this sorting flow (positive and negative) is shown in Figure 21.

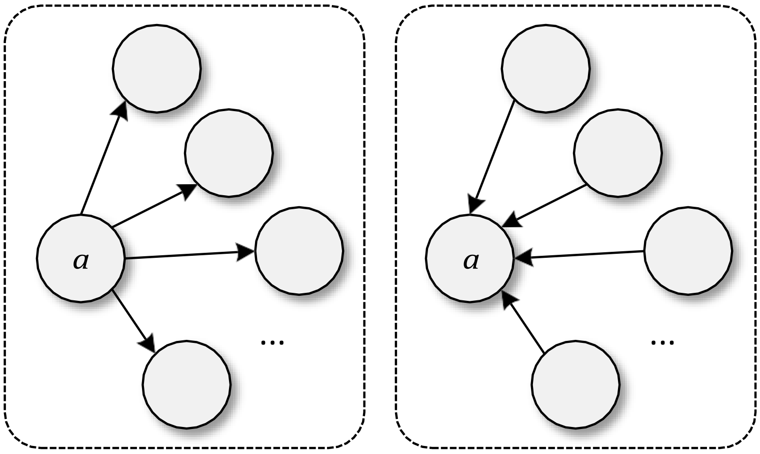


Figure 21. Sorting flow: positive (left) and negative (right). Adapted from [138]

Regarding the advantages and disadvantages, PROMETHEE presents as a differential the possibility of involving the decision at the group level, in addition to dealing with quali-quanti information, and incorporating uncertainties and fuzzy information in its analyzes. As weaknesses, this method does not structure the objective properly, it depends on the decision maker to give weight to the criteria and has a higher level of complexity than the AHP, requiring, in some cases, the presence of a specialist [132].

Similar to the AHP, PROMETHEE also compares the alternatives with respect to each other indicating the performance of each for a given criterion [53]. To carry out the PROMETHEE methodology it is necessary to calculate:

$$\prod(a,b) = \sum_{i=1}^{n} w_i * P_{i_{(a,b)}} \qquad (13)$$

Where:

$\prod(a,b)$ = Degree of preference of the alternative a with respect to b, for all the criteria;

w_i = Criterion weight $i(i = 1, 2, \dots, n)$;

$P_{i_{(a,b)}}$ = Preference function.

The preference function assumes values between 0 and 1 and are associated with each criterion indicating the preference between alternatives, and are represented as a function of the difference of the criterion before the alternatives, being chosen according to the problem together with the decision maker.

Once the degree of preference has been calculated, the value of the positive overshoot flow ($\emptyset^{+}$) should be measured, indicating how much better the alternative is to the others, while the negative ($\emptyset^-$) indicates how much the same option is exceeded by can be calculated with the formulas, considering A as the set of possible alternatives for the situation:

$$\emptyset^+_{(a)} = \frac{1}{n-1} * \sum_{b \in A} * \prod(a, b)\,, \qquad (14)$$
$$\emptyset^-_{(a)} = \frac{1}{n-1} * \sum_{b \in A} * \prod(b, a)\,. \qquad (15)$$

The PROMETHEE model provides an advanced modeling technique, but it has as prerequisite the need for precise information about the parameters.

Details with the formal mathematical definitions of the PROMETHEE method are further detailed in [53].

3.1.5 TOPSIS - Technique for Order of Preference by Similarity to Ideal Solution

Methods of MCDM developed to solve real-world decision problems, the Technique for Order Preference by Similarity with the Ideal Solution (TOPSIS) continues to function satisfactorily in several application areas [54]. The basic principle is that the chosen alternative should have the smallest distance from the ideal solution and the largest distance from the ideal negative solution.

For the application of TOPSIS, a sequence of calculations must be performed, following the traditional order, these are: development of the normalized decision matrix, development of the weighted decision matrix, distance to the positive ideal solution (PIS) and the negative ideal solution (NIS) and relative proximity.

The development of the TOPSIS method can be performed with the execution of 5 steps [54], as demonstrated below.

Step 1: Construct normalized decision matrix,

$$r_{ii} = \frac{x_{ij}}{\sqrt{(Ex_{ij}^2)}} \quad for \quad i = 1, \dots, m; j = 1, \dots, n \qquad (16)$$

Where x_{ij} and r_{ij} are original and normalized score of decision matrix, respectively.

Step 2: Construct the weighted normalized decision matrix

$$v_{ij} = w_j\, r_{ij} \qquad (17)$$

Where w_j is the weight for j criterion.

Step 3: Determine the positive and negative ideal solutions

$$A^* = \{v_1^*, \dots, v_n^*\}, \text{ Positive ideal solution} \quad (18)$$

Where $v_i^* = \{\max(v_{ij})\ if\ j \in J; \min(v_{ij})\ if\ j \in J'\}$

$$A' = \{v_1', \dots, v_n'\}, \text{ Negative ideal solution} \quad (19)$$

Where $v' = \{\min(v_{ij})\ if\ j \in J; \max(v_{ij})\ if\ j \in J'\}$

Step 4: Calculate the separation measures for each alternative. The separation measures from positive ideal alternative is:

$$S_i^* = [\sum(v_j^* - v_{ij})^2]^{1/2} \quad i = 1, \dots, m \quad (20)$$

Similarly, the separation from the negative ideal alternative is:

$$S_i' = [\sum(v_j' - v_{ij})^2]^{1/2} \quad i = 1, \dots, m \quad (21)$$

Step 5: Calculate the relative closeness to the ideal solution C_i^*

$$C_i^* = \frac{S_i^F}{S_i^* + S_i^F}, \quad 0 < C_i^* < 1 \quad (22)$$

Select the alternative with C_i^* closest to 1.

The TOPSIS method introduces two ‘‘reference’’ points, but it does not consider the relative importance of the distances from these points [55].

Details with the formal mathematical definitions of the TOPSIS method and examples of application are presented in [54.55].

3.1.6 Discussions

Decision making processes in companies are usually complex. Deciding something may take into account data from information systems and human knowledge (based on experience). In this context, multicriteria decision analysis helps the decision maker to solve problems with goals to be achieved simultaneously. MCDMs can be employed with qualitative, quantitative or hybrid information (quali-quanti).

There are several factors that can influence the decisions to be taken in the RCM deployment. The technologies available and the quantity and quality of the information are examples of factors that can make decisions difficult. Another important issue is related to critical aspects of industrial plants. In many cases, the systems are large and complex, making it difficult to decide the best options for decision-making processes.

In the present research MCDMs support the proposed "Smart RCM" model. The word "Smart" suggests, in this context, a methodology adapted with intelligence in decision making, reconciling qualitative and quantitative information in advanced models of MCDMs, to increase the reliability of the information and the answers in the implantation phases. They basically support the following activities:

- Selection of the best RCM indicators to be used later as evaluation criteria.
- Ranking of critical systems that can be applied by RCM.
- Classification of risks in the equipment / components of the system.
- Prioritization of Maintenance Significant Items (MSIs) for a customized intervention.
- Selection of appropriate maintenance strategies.

Since the decision models are composed of qualitative and quantitative criteria and are dependent on each other, the proposed RCM methodology provides information for all at the same time, with the quantitative slice being updated in real time, allowing a continuous review of the results. This information, which is a measure of company metrics, comes from a variety of data sources, including aspects of Industry 4.0, as reported in the next topic.

3.2 DATA, INFORMATION AND KNOWLEDGE

MCDMs methods can use qualitative and quantitative data, that have real importance in the industrial scenario, being a bridge for the correct decision-making in maintenance. Some researches refer to this collaborative approach with a view that when coming from reliable sources, data and information are important to the whole process.

To improve the quality of quantitative information, process mining techniques have been used to treat the raw information and improve the consistency of the available information. Process Mining can be defined as the discovery of knowledge by analyzing tasks execution logs [56]. It is used to verify the difference between what was going to happen and what actually happens. Process Mining have been applied in many areas, such as business processes, decision-making, software Engineering, etc. [56,57]. [58] proposed the use of mining for organizing and maintaining knowledge in a generic process. It consists in the creation of a system of knowledge collection and maintenance.

The quality of knowledge being generated is important for collaboration between levels of the organization. In this context, mining methods can be applied to review the maintenance records, discovering the process and assisting in creating of a model of optimal maintenance policies.

The use of mining techniques in data whose source is maintenance planning is proposed by [59]. A methodology using a mining approach to extract accurate fault rate data from WOs (Work Orders) and DD (Downtime Data) is presented by [60]. The purpose of these initiatives is to explore the available information, evaluating possible consistent patterns, such as association rules or temporal sequences, and detecting systematic relationships between variables. With this, the knowledge base to be generated becomes more robust and reliable, increasing the credibility of the decision-making.

Maintenance managers have access to large amounts of data and have a complicated task that is to turn that data into information that supports maintenance actions [59]. Important criteria include the need for multidisciplinary team building, decision support tools, reliability data, and assistive technologies [14,61]. In this context, publications involving CBM - Condition-Based Maintenance [62], risk assessment [63], TPM - Total Productive Maintenance [64] are examples of applied research to improve decision-making in maintenance.

3.2.1 Digital information for maintenance

Basically, digital information represents structured and unstructured data that is difficult to process using traditional database techniques and software. This is significant data for the scope of RCM to leverage all available information for use in analysis and decision making tools.

All the information available at all levels of companies is important for the application of the RCM methodology, which uses metrics from these intelligent systems. In addition, aspects related to reliability and safety are considered among the most crucial factors of the intelligent system, which are now challenged by the highly complex, automated and flexible industrial system. Industry big data analytics will have great benefits, such as improving performance, achieving near zero downtime, ensuring predictive maintenance and more [65]. In this context, Industry 4.0 is a current trend in the manufacturing domain, based on the concept of "smart factory". Among other organizational services, Industry 4.0 requires a quick and efficient maintenance service in order to guarantee that companies implement an efficient production system [66]. It is important to note that, in the case of large-scale multi-source data, the data can be used to predict reliability.

Modern systems based on Industry 4.0 requirements can operate with the support of a greater informational density and tools to support decision-making. The data that are collected with the aid of these systems are saved in clouds. Products integrated with cloud computing in the field can provide data that enable a predictive maintenance and provide information about optimization possibilities in production.

3.2.2 Structuring Data

The structuring of data is an important issue to be developed in the present research, which deals with the junction of available information. This approach is an important requirement for the development of the proposed Smart RCM. Figure 22 presents the sources of information and the processes for structuring the data.

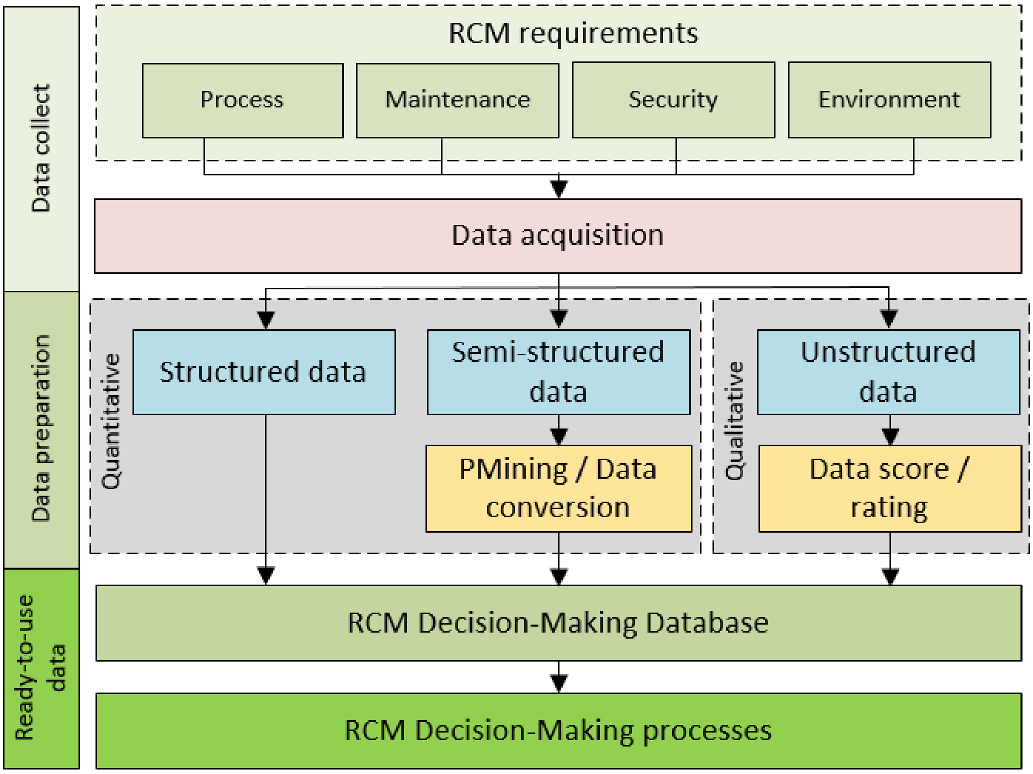


Figure 22. Acquisition and structuring of RCM data.

The upper layer of the Figure 22 shows the company elements from which the information is acquired, according to the RCM program. It is important that the data collected from the process has the necessary structure for the database. Quantitative data is considered structured (with the information or indicator format ready for use in analysis and decision making) or semi-structured (digital information, but not conforming to the standard format or unreliable). Qualitative data are considered unstructured and should be quantified using rating or score tables, according to their characteristics in the context of the company. The goal is to convert them into a measurable and calculable indicator format for later use in future RCM decision-making processes. To extract useful information from multisource data, unstructured and semi-structured information should be transformed into structured data in advance so that data barriers due to differences in source, format, dimension and other factors can be eliminated [65]. The methodology for creating the DMD will be presented and detailed in topic 5.2.

The quantitative data have a defined structure, requiring in some applications their correct treatment. Qualitative data needs to be structured based on raw information and expert experiences. Here are some examples of industrial data sources to be extracted to the RCM program [65]:

- Design data, such as data from the product and machine design.
- Machine operation data, such as data from the control system, equipment operation.
- Staff behavior data, such as manual operation record, staff working process videos.
- Cost information, such as cost of manufacturing process, operations.
- Fault detection and system status monitoring data.
- Product quality data, such as the defective rate of each facility.
- Product usage data, such as availability, repair rate.
- Customer information, such as customer features, feedback data, suggestions.

To support the preparation of quantitative information, Process Mining techniques are presented in the next topic. Its purpose is the treatment of raw information, recognizing patterns and relationships between data for structuring the RCM data process.

3.2.3 Process Mining

In production systems, a lot of data is stored by management systems in logs, such as events and failures. The use of process mining as an analytical tool to analyze it has been increasing in recent years and the emergence of new manufacturing paradigms such as the Industry 4.0 initiative have led many smaller manufacturers to look at utilizing these powerful techniques [67]. Although these data are correct, most organizations diagnose problems based on imaginary facts rather than actual plant behavior [68].

In this context, process mining techniques allow an analysis of this data to improve the quality of the information, detecting bottlenecks and arises to analyze these data and determine where, when and why the anomalies occurred in the system. It does not only allow companies to fully benefit from stored information, but also to use it to check compliance of process data, detect implementation problems, and predict hidden behavior. In addition, out-of-standard data can be filtered by increasing the reliability of the information.

For decision-making in industrial processes, information processing must be performed prior to the sending of collected data to the decision makers. The fusion of qualitative and quantitative information needs to be considered, using the tools available for each application. Figure 23 represents this process, presenting the ideal approach to be applied in decision-making [68].

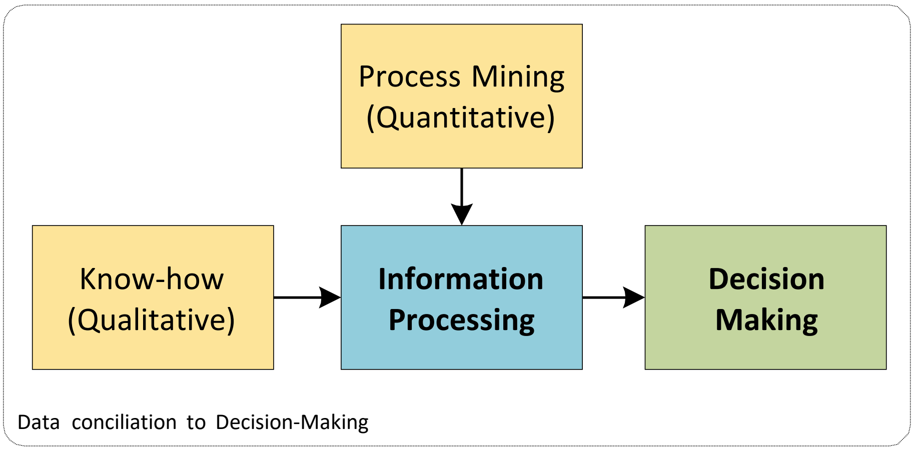


Figure 23. Ideal approach to decision-making [68]

The junction of the information under the presented aspects results in the creation of a knowledge base, which can be used in decision-making processes, developing data-driven business models and services, e.g. supply new contracts for production systems [69].

3.2.4 Prescriptive Analytics in Maintenance context

Optimizing the generation and organization of maintenance knowledge and decision-making in times of technological revolution enables improved availability and consumption of data and information efficiently. A structured approach and modern concepts are needed to improve information extraction and knowledge discovery. In this context emerges the Maintenance Analytics (MA) concept, that can be presented based on four interconnected phases (Figure 24): (i) Descriptive Analysis, (ii) Maintenance Diagnostic Analysis, (iii) Predictive Analysis and (iv) Prescriptive Analysis

[70]. The objective of facilitate maintenance actions through improved understanding of data and information.

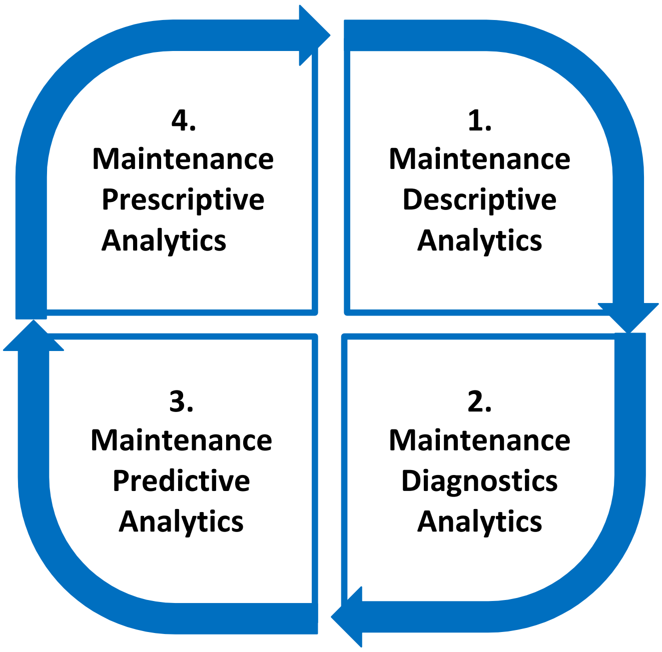


Figure 24: The four phases of Maintenance Analytics [70]

Basically, each phase of the Maintenance Analytics seeks to answer a question in the following sequence: (i) What has happened? (ii) Why something has happened? (iii) What will happen in the future? And (iv) What needs to be done?

According to [42], Descriptive Analysis aims to summarize what happened as simple event counters. The purpose of diagnostic analysis is to find out why it happened. Already the Predictive Analytics uses a variety of statistical, modeling, data mining, and machine learning techniques to study recent studies and historical data, allowing analysts to make predictions about the future. Still, Predictive Analytics cannot tell what will happen in the future, it can only predict what will happen in the future. And the emerging approach is Prescriptive Analytics (PRx), that can go beyond descriptive and predictive models, recommending one or more courses of action and showing the likely outcome of each decision. PRx is a component of the Industrial Internet of Things (IIoT), that can use machine learning and data revision automation to avoid equipment or device failures. Industry experts call this preventive maintenance with built-in intelligence [42].

3.2.5 Discussions

When looking at maintenance in the context of Industry 4.0, it is observed that little attention is being given to this area of study, as it presents the systematic review of the literature performed by [71]. The authors of this article infer that the academy is investing efforts on mainly related to manufacturing, management (in the PLC), design, programming and control - in this order. However, maintenance work focuses on technologies to optimize the process of transmitting information from the factory floor to time, such as the use of wireless devices for equipment, which would also reduce maintenance costs and dangerous [72].

The prognosis of production systems can be considered a valuable tool when it is desired to predict the useful life of the machines, involving the monitoring of conditions, fault diagnosis, operation / service time maintenance, and all these topics serve as an informational basis (scientific and technological) for decision making [73].

In this way, the data fusion of qualitative and quantitative indicators for decision is necessary and essential to guide the decision-maker to a more assertive and appropriate to the process analyzed, since, as already mentioned, the qualitative indicators will be obtained by tacit knowledge of the operator and the quantities will be extracted of event logs by means of process mining techniques. The combination of these two forms of analysis makes the analysis and interpretation of the system more robust and dynamism, given that the robustness will be achieved through the mutual fusion of quali-quanti indicators and dynamicity by the speed of the analysis of the data of the factory floor and possibility of these indicators during the decision-making process.

The smart-RCM framework to be presented aims to use current techniques for a modern and technological approach. In this sense, this research proposes the term "Smart RCM", that is, a maintenance application focused on reliability Industry 4.0. One of the premises of the fourth industrial revolution (Industry 4.0 or I4.0) is interconnect the machines of the factory floor (horizontal grid) and the organizational levels (grid vertical), transforming the company into a single / global system. In this context, the reliability of machines and cells is a required and extremely important function for optimize production, maximizing productivity and minimizing costs related to the operation.

Therefore, determining which maintenance strategy and tasks to apply (based on process indicators and tacit knowledge of the operator) is shown as a promising source of business differentiation. It creates a competitive advantage and confidence in the performance and preservation of the functions of the system, increasing its reliability.

In current scenarios, many companies consider maintenance management to be a production activity, so good management can sector and boost the company's business, obtaining the competitive advantage [74]. In addition, Smart RCM provides for adequate and optimal use of resources (operators, tools, machines, etc.) available in the process, aiming at the assertiveness of the choices.

In order to support the decision models used in this Smart RCM approach, a systematic review of the literature is carried out, seeking, in contemporary approaches, the indicators / metrics used in applications. Details of this analysis are presented in the next section.

4 MAPPING METRICS FROM RCM APPLICATIONS

According to task 2 of the IDEF0 model presented in Figure 3, one of the initial stages of the research proposes the creation of a database with indicators to be consumed by the RCM decision stages. For this, we analyzed relevant scientific bases for the mapping of works developed with models of RCM implantation and their indicators.

The literature review was based on 3 stages (Figure 25): (i) planning: identification for the RCM implementation models and indicators and development of a review protocol; (ii) execution: review implementation and creation of an organized scientific base; and (iii) assessment: phase in which a detailed study is carried out in the works selected by the protocol.

In this last phase, a bibliometric analysis is performed to support the results and improve visualization of the researches problem space. Methodological, operational and results aspects are verified and presented, generating important discussions for use in next sections.

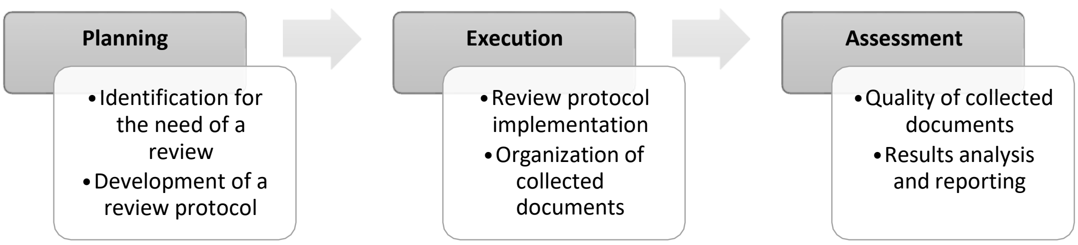


Figure 25. Stages of a Systematic Review

A review protocol shows information about the research fields and selected criteria for the selection of manuscripts that have relevance in a given topic in the scientific community [75]. Thus, in order to analyze the recent research in RCM under the inference of models and indicators, a research protocol was developed. For its preparation, the information was used in three dimensions: (i) the RCM methodology; (ii) implementation terms and (iii) words that refer to the indicators/metrics. A Boolean operation OR was done between the words of each dimension and the operation AND between the groups.

Table 2. Systematic Literature Review Protocol

Keywords	Group 1 (RCM) – RCM, Reliability Centered Maintenance. Group 2 (Application) – Framework, Deployment, Case Study, Implementation, Development, Application. Group 3 (Indicators) – Indicators, Measures, Metrics, Assessment, KPI, Measurement.
Databases	Science Direct, Emerald, Scopus, Web of Science.
Boolean Operator	OR between the words of the Group 1; OR between the words of the Group 2; OR between the words of the Group 3; AND between Group 1, 2 and 3.
Exclusion Criteria	Duplicate Papers; Papers with scope different than Engineering and industry; Books and e-books;
Language	English
Publication Type	Papers from journals
Time Window	2007-2018

Four large scientific databases were explored and only works in article format were selected. Still, in order to analyze only contemporary research, were considered only surveys published after the year 2007. The execution of research protocol resulted on 222 papers founded. After applying the exclusion criteria of the review protocol, 30 articles were assessed as the most relevant to the research, meeting all requirements previously planned. Figure 26 shows the quantitative flowchart of the execution of the research protocol.

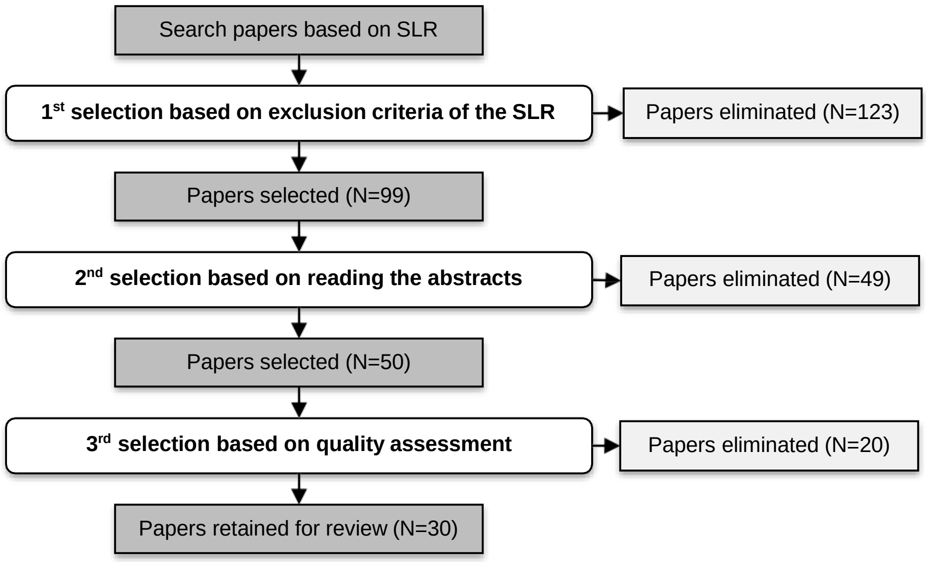


Figure 26. Papers selection flowchart

4.1.1 Bibliometric Analysis

It is important to carry out a bibliometric analysis, in order to verify the studies extracted from the research protocol in a general and quantitative way. In this initial phase of analysis, the articles were organized by the journals where they were published (Figure 27), by the year of publication (Figure 28) and by the industrial sectors (Figure 29), since the focus of the research were articles with studies on the shop floor. In addition, Figure 30 shows the most commonly found keywords, mapping a terminology already expected before the development of proposed research protocol.

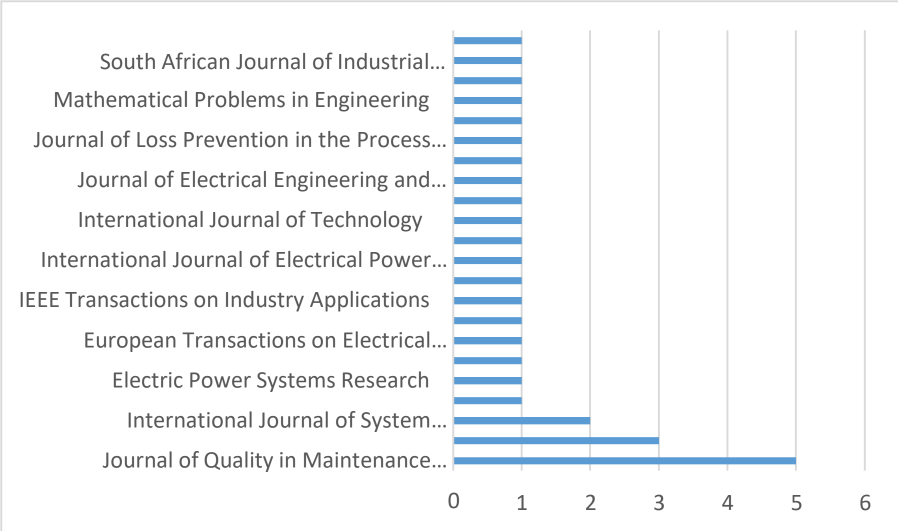


Figure 27. Number of publications by periodic

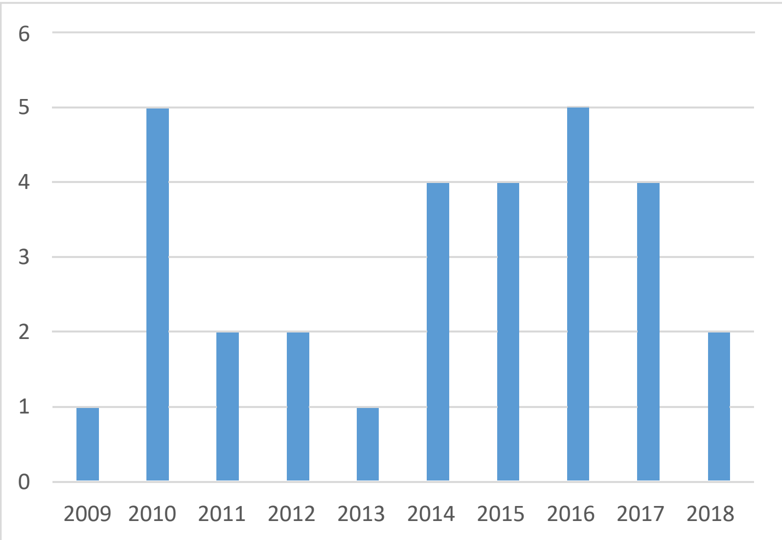


Figure 28. Number of publications by year

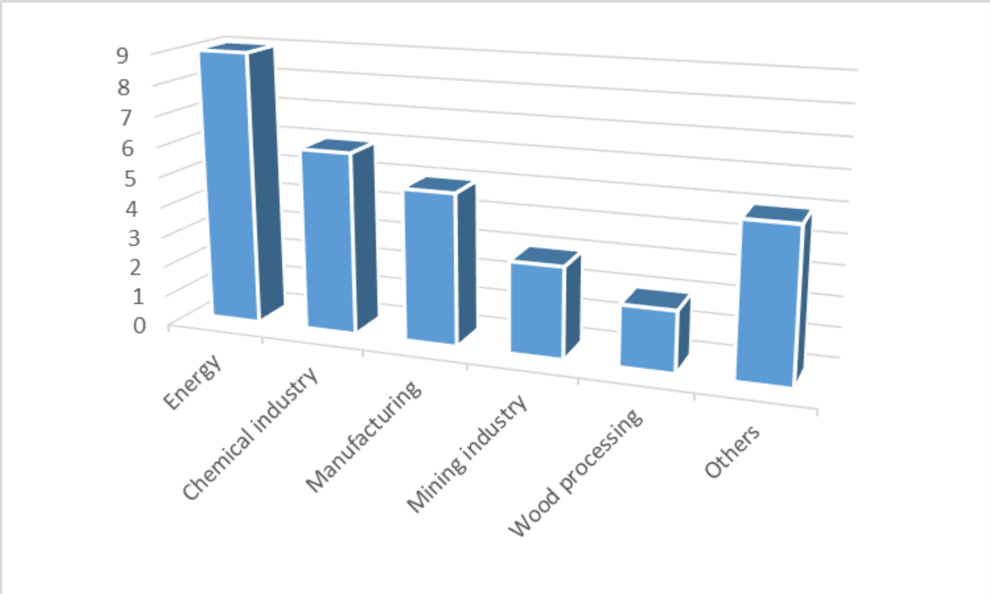


Figure 29. Distribution of publications by sector

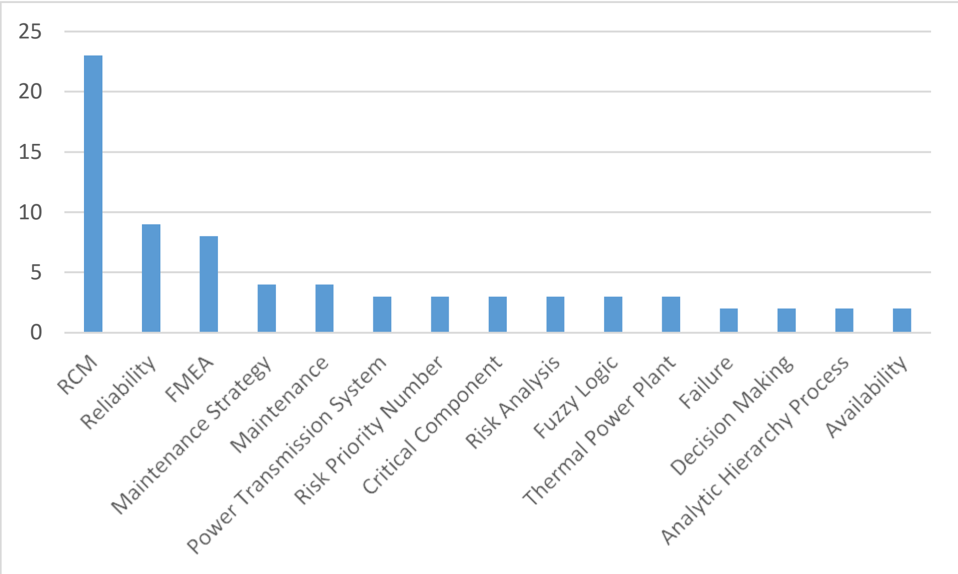


Figure 30. Most cited keywords

A complete reading of the articles allowed to know the methods and tools used in each application, and the extraction of the indicators used to develop and evaluate the RCM program. Indifferent to the industrial segment, the concern of the authors of the research is centered, as the methodology proposes, in increasing the reliability and availability of the equipment through the reduction of failures, bringing, in some applications, concerns with personal and environmental safety, according to the mapping carried out in the topics to follow.

4.2 MAPPING SMART RCM METRICS

The review was developed for the mapping of the metrics used in RCM applications. The main indicators were extracted from the articles and organized. In a first survey 50 indicators were extracted and after careful analysis it was verified that many of them, although presented with different names, referred to the same indicator. Thus, a step of joining the indicators was performed, which resulted in 25 different indicators, according to Figure 31.

LIST OF INDICATORS ↓		PAPERS ID ↓																													
Ind ID	Indicator	[76]	[77]	[78]	[79]	[80]	[81]	[82]	[83]	[84]	[85]	[86]	[87]	[88]	[89]	[90]	[91]	[92]	[93]	[94]	[95]	[96]	[97]	[98]	[99]	[100]	[101]	[102]	[103]	[104]	[105]
#01	Availability		X		X			X			X	X			X			X	X				X			X			X		
#02	Detection Rating	X					X				X										X	X		X				X			X
#03	Mean Downtime		X	X							X	X	X		X		X		X				X				X			X	
#04	Economic Cost Risk		X																												
#05	Environmental Risk		X	X									X						X											X	
#06	Failure rate (λ)		X		X			X	X	X			X	X	X	X	X	X	X	X	X			X	X		X			X	
#07	Maintainability		X									X	X									X	X								
#08	Maintenance Cost		X		X			X		X	X								X	X			X	X			X			X	
#09	Mean Time Between Downing Events																									X					
#10	Mean Time Between Maintenance																									X	X				
#11	Mean Time To Failure																		X					X		X					X
#12	Mean Time To Repair		X		X			X	X		X	X	X			X	X	X	X				X		X	X	X				X
#13	Mean Uptime																														
#14	Number of Failures				X			X			X			X					X	X					X						
#15	Occurrence Rating	X					X							X										X				X			X
#16	Overall Equipment Effectiveness										X												X								
#17	Probability of Failures	X	X	X	X			X				X				X			X					X						X	X
#18	Production Cost			X	X			X	X	X									X	X	X		X								X
#19	Reliability				X			X				X		X		X		X					X	X	X			X	X		
#20	Safety Risk		X	X							X								X												
#21	Security Cost				X			X																							
#22	Sensor measurements																			X									X		X
#23	Severity Rating	X	X				X							X										X				X			X
#24	Time To Failure																											X			
#25	Total Operation Time																								X						

Figure 31. RCM indicators mapped

The information extracted from this survey presents a numerical identification of each indicator, represented by "Ind ID", to facilitate the presentation and allocation in the next sections. Figure 32 presents the characterization of the indicators with regard to the type of information was performed, being divided into qualitative and quantitative indicators, as well as their respective units of measurement and a brief description.

LIST OF INDICATORS ↓		FEATURE ↓		MEASURE ↓	
Ind ID	**Indicator**	**Quali**	**Quanti**	**Unit**	**Description**
#01	Availability		X	Percentage	Percentage of total hours or scheduled time of where a machinery or system is available for production.
#02	Detection Rating	X		Level/Weight	Measurement of the possibility of a failure of a system, machine or equipment to be identified.
#03	Mean Downtime		X	Time	Average time that a system is not available for operation.
#04	Economic Cost Risk	X		Level/Weight	Economic risk related directly to downtime.
#05	Environmental Risk	X		Level/Weight	Measurement of impacts caused by physical, chemical or biological agents that can cause consequences to the environment.
#06	Failure rate (λ)		X	Failure/time	The average of how often a component, equipment, or system fails in a given time period.
#07	Maintainability	X		Level/Weight	Level of facility for maintenance of machinery.
#08	Maintenance Cost		X	$	Effective cost of maintenance employed in each system asset.
#09	Mean Time Between Downing Events		X	Mean time	Expected mean time between two consecutive events for a repairable system.
#10	Mean Time Between Failures		X	Mean time	Mean time between failures on a system or asset.
#11	Mean Time To Failure		X	Mean time	Mean time an asset will operate before it fails (average asset life).
#12	Mean Time To Repair		X	Mean time	Mean time for repair of any asset.
#13	Mean Uptime		X	Mean time	Mean time an equipment, machine or system is fully operational or ready to perform its function.
#14	Number of Failures		X	Quantify	Quantitative of failures in a asset.
#15	Occurrence Rating	X		Level/Weight	Likelihood of occurrence during production.
#16	Overall Equipment Effectiveness		X	Percentage	Percentage of time the machines are able to produce at full capacity, with products within the specified specification.
#17	Probability of Failures		X	Percentage	Probability expressed as a percentage in which a component or system fails.
#18	Production Cost		X	$	Any expenses associated with the business activity of an organization.
#19	Reliability		X	Percentage	Probability that an equipment or component will perform its function without failures over a period of time.
#20	Safety Risk	X		Level/Weight	Measurement of risks related to personal and organizational security.
#21	Security Cost		X	$	Expenses related to the implementation and maintenance of security related resources.
#22	Sensor measurements		X	Percentage	Measurements of process variables used in predictions of failures.
#23	Severity Rating	X		Level/Weight	Classification of the severity of the failure under aspects of safety, environment, production and costs.
#24	Time To Fail		X	Time	Estimated time for failure to occur based on time-based maintenance.
#25	Total Operation Time		X	Time	Measurement of the total operating time.

Figure 32. Characterization of mapped RCM indicators

Quantitative indicators are those obtained through numbers and exact data that are achieved through measurement, tabulation of reports, control and information systems among others. The qualitative ones are those that are more subjective, that start from the observation of the evaluator or coordinator of the project and there are no exact metrics to measure them, but there are methodologies for their treatment.

The following is the organization and characterization of the base of mapped indicators, with the purpose of improving the interpretation and use in the decision models used in this research project.

4.3 ORGANIZING AND FEATURING AND INDICATORS

Indicators are essential items for the planning, execution and maintenance of any project, as they assess the feasibility of decision-making, how these should be carried out and whether they have been efficient and effective [106]. They can be indexes, metrics, collection of qualitative and quantitative information that are able to indicate the results obtained through the development of the actions and reach the established goals and objectives [107]. It is presented on Figure 33 [106], that summarize the maintenance objectives under five headings: (i) ensuring the plant functionality (availability, reliability, product quality, etc.); (ii) ensuring the plant achieves its design life; (iii) ensuring plant and environmental safety; (iv) ensuring cost effectiveness in maintenance and (v) effective use of resources (energy and raw materials). We assume that the maintenance objectives pursued at a given plant influences the kind of performance indicators used.

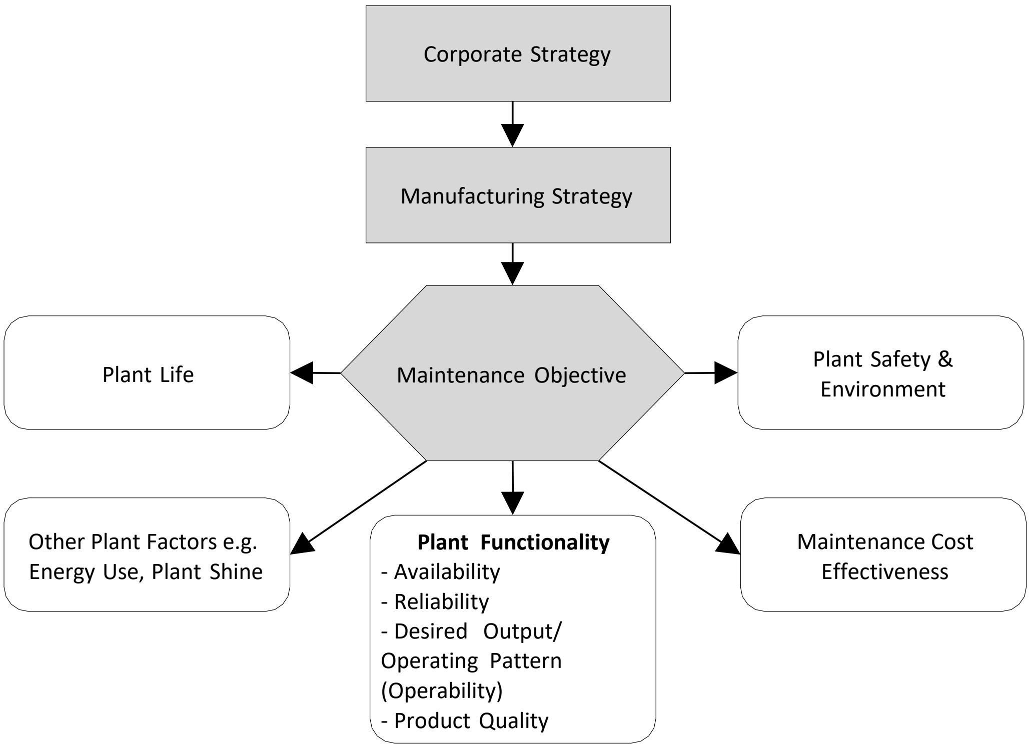


Figure 33. Maintenance objectives for a maintenance department.

Measurement metrics are not adapted to real needs, which have a strong human factor; nor is there a roadmap of the amount of data to be collected, their processing or how they are used in decision-making [108]. The qualitative indicators are those that are subjective, based on the observation of those involved with the project. There are no exact metrics to measure them, but there are methodologies that support their correct use. In order to better explain the characteristics of the indicators, they were classified as qualitative or quantitative and the measurement units used in each case were also raised. These aspects are important to support the choose the appropriated indicators to be used in the implementation of the RCM.

4.3.1 Indicators grouping

Analyzing the context of the surveys and the results of the extraction of the indicators, and based on study of [107] four groups were created for better organization and visualization: (i) Equipment Performance Measures; (ii) Costs Measures; (iii) Process Performance Measures and (iv) Risk Assessment Measures. The criteria for this organization were extracted from the literature, with the grouping based on the characteristics of the indicators. The group resulted are presented in the Figure 34 and detailed as follow.

GROUP	INDICATOR	
Equipment Performance Measures	#06	Failure rate (λ)
	#07	Maintainability
	#09	Mean Time Between Downing Events
	#10	Mean Time Between Maintenance
	#11	Mean Time To Failure
	#12	Mean Time To Repair
	#14	Number of Failures
	#16	Overall Equipment Effectiveness
	#17	Probability of Failures
	#22	Sensor measurements
	#24	Time Before Failures
Costs Measures	#04	Economic Cost Risk
	#08	Maintenance Cost
	#18	Production Cost
	#21	Security Cost
Process Performance Measures	#01	Availability
	#03	Mean Downtime
	#13	Mean Uptime
	#19	Reliability
	#25	Total Operation Time
Risk Assessment Measures	#02	Detection Rating
	#05	Environmental Risk
	#15	Occurrence Rating
	#20	Safety Risk
	#23	Severity Rating

Figure 34. Indicators groups distribution

Equipment Performance Measures

Indicators that submit to the performance of the maintenance function, under aspects of optimization of the use of available resources, analysis of failure and repair times and difficulties in performing maintenance tasks. The metrics in this group have characteristics that support tactical and operational levels [105,109]. The RCM methodology can absorb such indicators to analyze failures and their effects, as well as in program audits, verifying the results after their implementation.

Costs Measures

Cost analyzes are concentrated at strategic levels of the company. This group of indicators supports decision-making made by the managers of the production process, involving the production, maintenance and utilities sectors, encompassing environmental and safety aspects (risks) [107]. Due to the complexity of the RCM program, it is important to prioritize these measurements to indicate which systems are most important for the concentration of implementation and maintenance efforts.

Process Performance Measures

Global Performance Indicators integrate this group, which focuses on reporting how the production system behaves under aspects of availability, downtime and uptime, reliability and quality [107]. They are indicators that can be used in decision-making at all levels of the company. In RCM they can be used both for global performance measurements, for critical system selection, and for tactical and operational approaches such as risk measurement and prioritization of maintenance activities.

Risk Assessment Measures

The indicators that make up this group have been commonly used in industrial systems for decision-making, with the aim of mitigating or eliminating potential sources of environmental, operational and safety risks [109]. The risk measurements are predominantly inserted in fault analysis and its effects, for MSIs (Maintenance Significant Items) classification. As the central phase of RCM development, risk analysis defines important outputs for the selection of best maintenance practices.

The groups will serve as a basis for the subsequent use of the indicators in the implementation phases of the RCM, providing an overview of all aspects considered important for the execution of decision-making processes.

4.4 DISCUSSIONS

The mapping of the indicators performed by the systematic review presented is an important step in the construction of the Smart-RCM model. For the better implementation of the methodology this "menu" provides metrics that are often not observed by the managers of the company. We have opted for a review of contemporary works, given the advances in information systems of companies in the last decade.

The information extracted from the literature points to a diversity of qualitative and quantitative indicators used to evaluate performance and criticality, with applications in several segments. These data are used for the implementation of the RCM methodology and for further evaluation and feedback. Still, with the separation of the indicators into groups, the selection becomes easier, generating an organization with the mapping in areas of the process.

This indicator base is verified by a team of experts at the beginning of the RCM deployment. After this availability analysis, the construction of the information base to be used starts, with the selection of the most important indicators for the decisions to be taken in the implementation of RCM, according to the strategies of the company.

It should be noted that the review was carried out in several scenarios, but some companies have specific and customized indicators that must be analyzed and inserted in the methodology.

The next section (5) presents the steps for creating the proposed Smart-RCM model, and topic 5.3 demonstrates the methodology for creating this base of metrics to be used in the decision steps of the proposed framework.

5 SMART RCM DEPLOYMENT MODEL

Around the world, RCM is considered an imperative technology in the industry maintenance field that can be functional to improve the equipment availability and reliability and reduce operational and maintenance costs [72]. To take advantages about it, the RCM classical approach seeks to answer seven questions presented sequentially on the system or process analysis: (i) What functions should be preserved? (ii) What are the functional failures? (iii) What are the Failure Modes? (iv) What are the effects of failure? (v) What are the consequences of failure? (vi) What are the applicable and effective tasks? (vii) What are the other alternatives? To answer these questions systematically, RCM program process in maintaining a device or system can be summarized in steps, according with models (norms and publications), as examples shown in Figure 35a [49] and 35b [25].

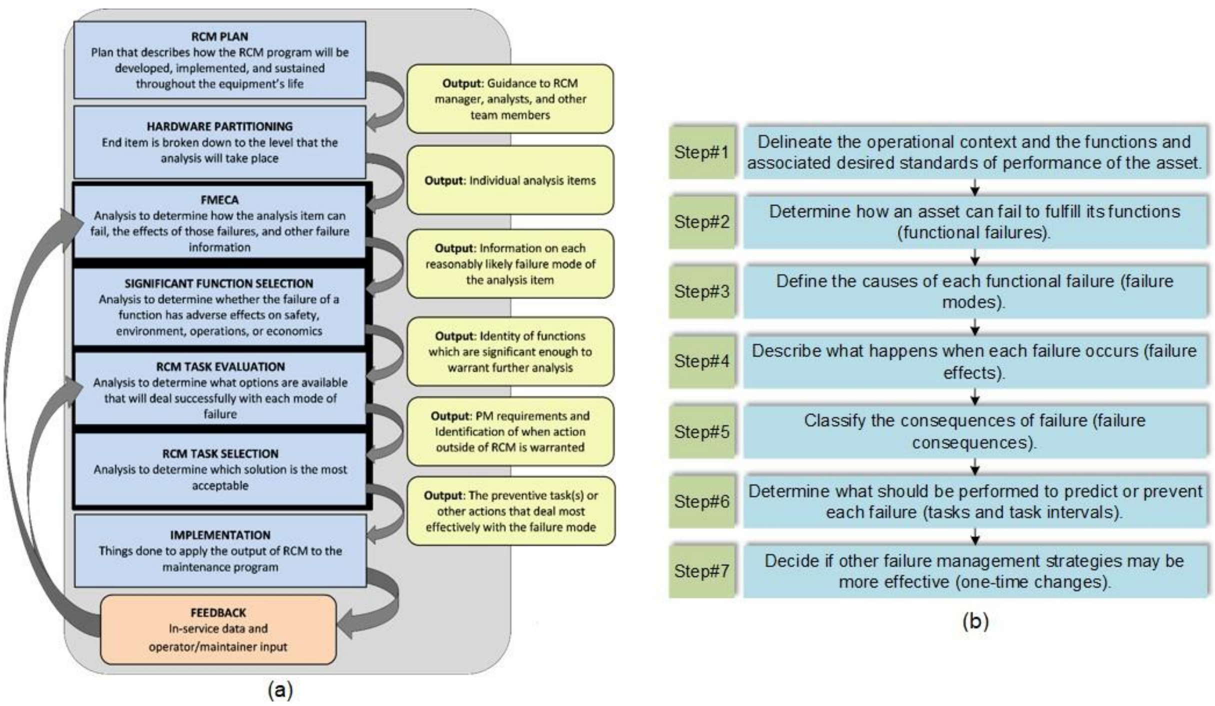


Figure 35. Examples of classical standards for RCM deployment

Each phase of RCM model is composed of inputs, controls, mechanisms and outputs, that forms an information flow. The information generated after the RCM implementation is made available to the model for continuous improvement.

5.1 CONCEPTUAL MODEL FOR SMART-RCM

A miscellaneous of information with qualitative and quantitative characteristics is available in all phases of RCM analysis. At each stage there is predominance the generation of tacit or explicit knowledge, or mixed approaches. Thus, based on the RCM implementation models presented in Figure 35 was developed a comparison mapping of the knowledge type used in the deployment phases as well as scope of analysis (Table 3).

Table 3. RCM: steps, knowledge type and scope of analysis.

RCM Step	Knowledge		Scope of analysis
	Tacit	Explicit	
RCM Plan	X	X	Analysis of individual and collective tacit knowledge and skills, to the RCM team establishment and program management, analysis and sustainment. Tacit knowledge is applied to choice the level of analysis, knowledge-based of RCM team experts. The explicit knowledge is used in the selection of the system to be analyzed, investigating the MSIs (Maintenance Significant Items), like the KPIs (Key Performance Indicators). Quantitative data is important in this phase to identify the critical systems based on process parameters and maintenance and process indicators.
Hardware partitioning	X		Logical division of an item into subsystems and progressively smaller elements (components) those are decreasingly complex. It is a step based on tacit knowledge from team experts.
FMECA	X	X	Tacit knowledge is used in identification and analysis of functions, failures, failures modes and criticality, being a predominant approach in this step. Explicit knowledge is employed in FMEA or FMECA extensions, with analysis of process parameters, criticality and risk assessment.
Significant function selection	X		Consists in the analysis of failure effects on safety, environment, operations, or economics requirements. Tacit knowledge is applied in qualitative decision tools, like logic diagrams.
RCM task evaluation	X	X	Tacit knowledge is an important information source to determine which of several options is best suited to prevent a failure mode from occurring or, if not preventing it, to reduce the consequence of its failure to a level that is acceptable to the program. The evaluation of the efficiency of the maintenance tasks commonly use explicit knowledge from maintenance indicators and apply in decision-making approaches, to choice the best maintenance policies and techniques.
RCM task selection	X	X	Tacit approaches are applied at this stage using specialist's responses on decision diagrams, proposals for RCM standards, and publications. The use of explicit knowledge, extracted from maintenance and process indicators, when available, supports decision making in choosing the best maintenance strategies.
Implementation	X		The RCM Implementation Manager use tacit knowledge to establish a method of review and approval that ensures the RCM methodology and to verify continuously if the RCM program is

	properly and effectively applied, maintaining audit trail of RCM recommendations and implemented actions.

The steps for the RCM implementation use knowledge extracted from various information sources, from questionnaires answered by the implementation team to quantitative data (indicators, metrics) stored in information systems. As these steps are structured sequentially, the present research proposes a new structure that does not exclude the tasks, but concentrates them, composed by activities analogous to the classic RCM model presented.

Thus, a customized RCM model is proposed, with an emphasis on knowledge fusion. The objective is to facilitate the implementation process, focusing on the data fusion of qualitative and quantitative indicators, improving the available knowledge for decision making. This model performs the steps presented earlier in Figure 35, joining them into three phases of implementation: (i) RCM Planning (steps 1 and 2); (ii) Failures, effects and criticality analysis (steps 3, 4 and 5) and (iii) Strategy definition and analysis (steps 6 and 7). Figure 36 presents the proposed model. The three phases are detailed on section 6.4.

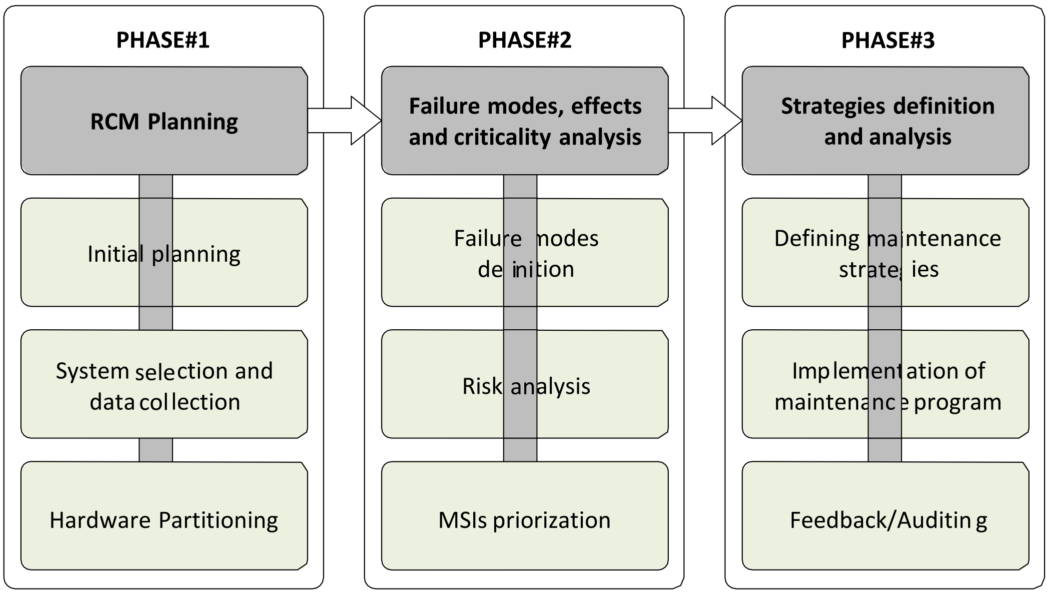


Figure 36: RCM deployment flow

The present RCM model has a decision-making approach. The layers of the company, from the factory floor to the management, have different levels of interaction with the processes. According to [109], multiple indicators should be associated with every level. One layer of indicators could be at the corporate level, and another at the departmental level. [110] proposes the division of the company into three organizational layers: operational, tactical and strategic. Figure 37 shows the indicators groups, their allocations in the business layers and their relationships with the development of the RCM program.

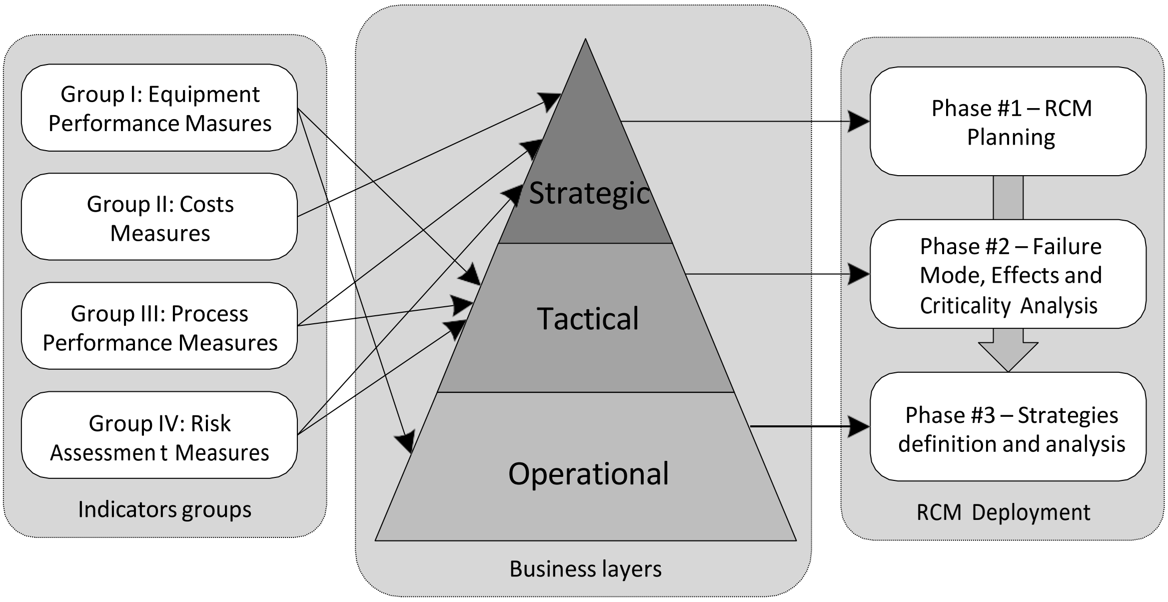


Figure 37. Relationship between indicators, industrial layers and RCM

Strategic level concerns the provision of productive resources to ensure the company's competitive capabilities. This involves monitoring technological changes and weighing economic factors and investment criteria. Tactical level addresses effective resource utilization and involving the availability and reliability of production equipment as well as finding optimal maintenance policies. Operational level deals with day-to-day operational and scheduling decisions. This involves prioritizing jobs and considering the availability of workers, spare parts, tools and the equipment to be maintained.

5.2 DECISION-MAKING DATABASE – DATA FUSION APPROACH

The SAE JA1011 standard [24] recognizes RCM as a dynamic program, where many of the data used in the initial analysis of RCM are inherently inaccurate, and more accurate data will be available over time. The way the asset is used, coupled with the associated performance expectations, will also change over time. In this context, the Decision-making Database is the initial collect and treatment of qualitative and quantitative data.

Qualitative data consists in information based on experience from experts. The sources of this type of data can include relationships, observations, reports, norms, values, operating standards and maintenance procedures. It can be collected using forms, questionnaires, interviews, etc. Quantitative data can be extracted from maintenance indicators, archives, information systems like CMMS (Computer Maintenance Management System) and EAM (Enterprise Asset Management), data logs, process data (sensors, controllers and actuators), smart devices and data sources included related to Industry 4.0.

There are several tools and methods for explicit data collection, but they are not always available in all processes. Process mining is an important approach to analyze this data source and validate it, transforming the quantitative information in a reliable information source.

From the design of the RCM methodology to the proposed model, an initial step for the creation of a dynamic database should be implemented, according to Figure 38. Consists in the fusion of qualitative and quantitative information to feed the Decision-making Database (DMD), which will store the MCDM inputs in the RCM steps.

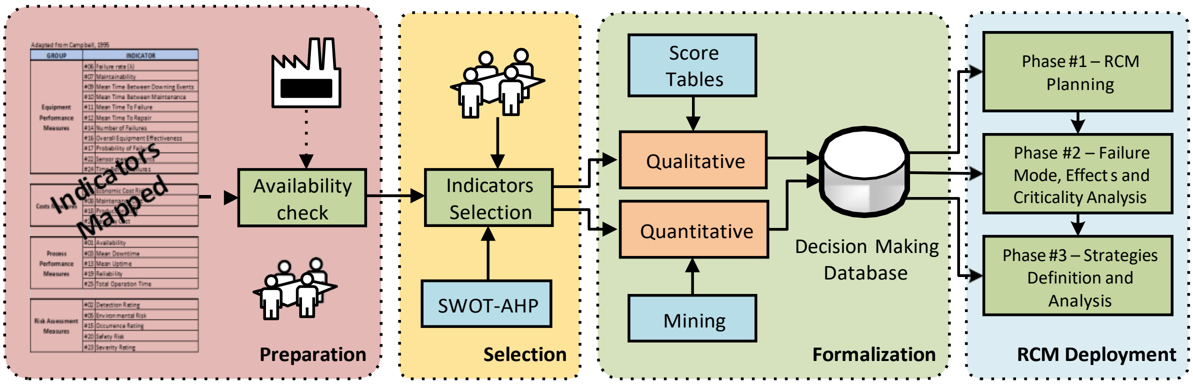


Figure 38. Decision-making Database to Smart RCM deployment

This module comprises the following steps: (i) Preparation; (ii) Selection; (iii) Formalization and (iv) RCM Deployment. The following topics detail each step from DMD.

5.2.1 Preparation step

The indicator groups were mapped based on the literature, serving as the basis for the implementation of the RCM. However, it is necessary to perform an analysis and selection of the indicators to be used, according to the availability and importance of certain metrics for the company. The quality and availability of the metrics depends on the level of maturity of the company.

Thus a verification of the existence of the data should be the first step in the creation of the base of indicators that will be used for the RCM analysis. This evaluation should be performed by the managers of the implementation, with the support of a team of specialists. This is a correlation between the groups of mapped indicators and those available for use.

5.2.2 Selection step

After this verification, a prioritization of the indicators to be used should be performed, based on criteria defined by the team of experts. In order to support the selection of indicators, it is proposed to use criteria related to the company's level of maturity under two aspects: (i) Classical RCM requirements and (ii) Asset Management (related to Industry 4.0).

Classical RCM requirements criteria

For the use of indicators of the classic application of the RCM was used as reference the NASA RCM Implementation Guide [31], that provides considerations about the metrics to be used in the development phases of the program. Managers of the processes involved in the possible deployment of RCM should be involved in the selection of Key Performance Indicators (KPIs) for the continuous collection of data that will support maintenance. This is so that the company's goals and concerns are identified. Consideration should also be given to the cost of obtaining the data and how much they add to the RCM program. Based on these issues, the criteria used in the classical RCM approach are based on maintenance and operation considerations, described as: (i) Labor Force, (ii) System Experts, (iii) Training, (iv) Equipment and (v)

Maintenance History [31]. It is proposed the addition of risk criteria, described as (vi) influence on safety and (vii) environmental impacts [14].

Asset management criteria

In order to create a new culture of risk-based asset management the present Smart RCM program proposes the use of ISO 55000 standard [111]. According to this standard, the factors that influence the type of assets that an organization requires to achieve its objectives, and how the assets are managed, include the following: (i) the nature and purpose of the organization, (ii) its operating context, (iii) its financial constraints, (iv) regulatory requirements; (v) the needs and expectations of the organization and its stakeholders. The criteria listed for RCM analysis under aspects of asset management were based on these definitions.

The actions to address risks and opportunities associated with managing the assets, taking into account how these risks and opportunities can change with time, by establishing processes for [111]:

- identification of risks and opportunities;
- assessment of risks and opportunities;
- determining the significance of assets in achieving asset management objectives;
- implementation of the appropriate treatment, and monitoring, of risks and opportunities.

To better present the proposed criteria for the selection of the indicators are presented in Table 4. It is important to emphasize that the use of which can be customized by the analysis group.

Table 4. Criteria to indicators selection

Criteria	
Classical RCM	**ISO 55000**
Labor Force	Business context
System Experts	Operating context
Training	Financial constraints
Equipment	Regulatory requirements
Maintenance History	Needs and expectations
Safety	
Environment	

Next, the indicator selection phase is an organizational approach to the decision-making process with a hybrid SWOT-AHP model, according to the flowchart shown in figure 39, adapted from [112].

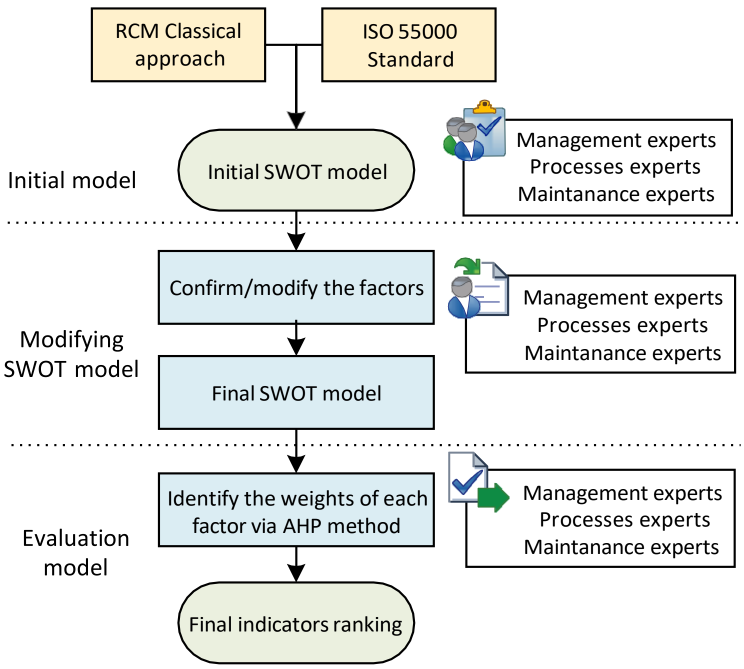


Figure 39. SWOT-AHP flowchart. Adapted from [112]

First of all, an initial model is built by the process management experts. The SWOT matrix is built using factors, which will be the evaluation criteria, based on the classic RCM model and the ISO 55000 (asset management) standard. Then the built model passes through an evaluation by the same team that modifies or adapts it according to the objectives of the company. Then the weights of each criterion are defined using the AHP method, performing a ranking of the indicators.

In the proposed model the SWOT analysis should be performed, analyzing and classifying the appropriate indicators for each step where multi-criteria decision-making methods are employed. The Figure 40 presents an example of the criteria distributed in the four SWOT groups.

		Strengths		**Weaknesses**
Internal environment	S#1	Equipment	W#1	Training
	S#2	Operating context	W#2	Needs and expectations
	S#3	System Experts	W#3	Safety
	S#4	Maintenance History		

		Opportunities		Threats
External environment	O#1	Environment	T#1	Regulatory requirements
	O#2	Labor Force	T#2	Business context
			T#3	Financial constraints

Figure 40. Example of SWOT analysis

To optimize the selection of indicators, an approach is proposed using the SWOT analysis and the AHP in a hybrid method. The goal is to improve the company's vision and optimize decision making. The use of the proposed SWOT-AHP method is important for the analyzes of the samples included in the SWOT analysis and make them commensurable. While the SWOT analysis shows the current situation, the AHP measures a methodology referring to SWOT factors [17,18]. By joining the SWOT and AHP, an evaluation of the alternative options and a mutual weighing of SWOT factors can be integrated with common analyzes. Thus, a more evident SWOT weakness can be avoided [19].

The hierarchy for the present research problem has been structured in four levels. The first level is the main goal will be achieved by the decision: to select the best indicators to use in RCM phases. The second level consists of decision objectives such as to take advantage of the Strengths, to reinforce the Weaknesses, to use the advantage of Opportunities and to develop the best defense to the Threats. At the third level SWOT factors described in SWOT analysis take part in. Finally, the fourth level consists of alternative indicators. A graphical representation of the hierarchical structure we used in this study is presented in Figure 41.

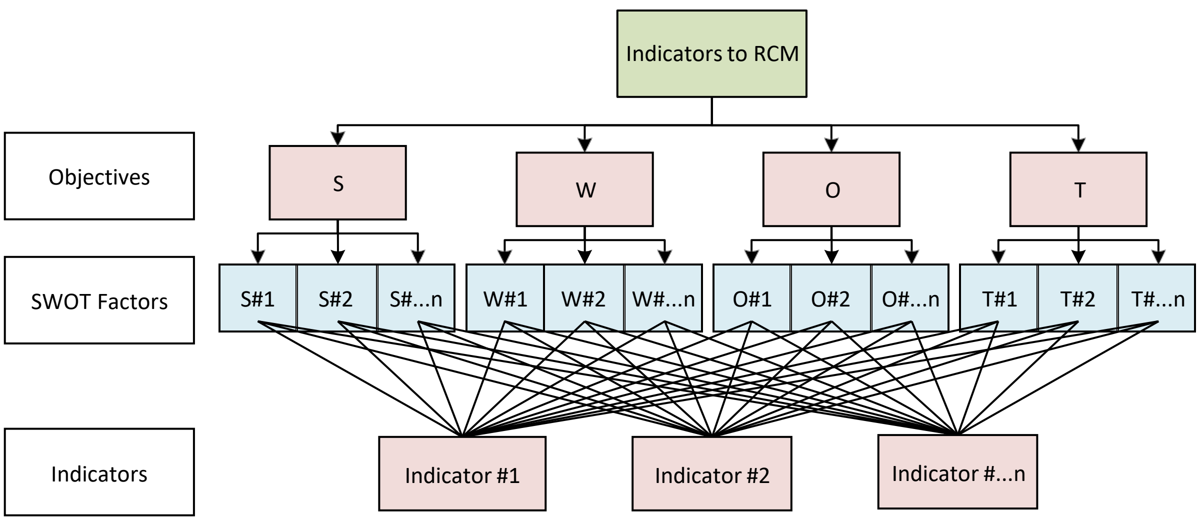


Figure 41. Hierarchical structure to SWOT-AHP approach

To limit the amount of indicators selected, some tool should be used, according to the opinion of the deployment team. Applying the Pareto chart may be a good option to determine this cut line.

The decision-making process should be carried out in three dimensions (performed three times), taking into account the indicators that will be priorities for MCDM models of the three phases of deployment, according to Figure 33. The team that will be part of the analysis should also be defined respecting the layers of the company (strategic, tactical and operational).

The characterization of the indicators should be performed based on their units of measurement, being divided between qualitative or quantitative, so that they are properly analyzed and formalized, as reported below.

5.2.3 Formalization step

For the preparation and organization of the information to be used in the RCM implementation the qualitative indicators go through a process of scheduling, through the creation of scoring tables. For this, the Saaty scale is used [113], which relates intensities with definitions, generating tables that will be answered by the decision makers when in multicriteria decision-making. On the other hand, the quantitative data are analyzed by process mining, in order to analyze outliers or deviations associated with the objectives of the indicators. With this, this information can be treated or discarded, increasing the reliability of the data used.

All information is allocated in the DMD (Decision-Making Database). The qualitative information will be entered manually, while the quantitative information will be automatically collected from datalogs of the company's Information System (IS). Updating the information should be performed at pre-defined intervals, according to the capabilities and guidelines of the company.

5.2.4 Towards the Smart-RCM Deployment

All the dynamic information of the indicators stored in the DMD will be used in RCM deployment, in steps that are the development phases. They will serve as inputs to the MCDMs that will have their decisions changed dynamically, influencing their respective outputs (classification, prioritization, etc.). The following topic presents the proposed conceptual model, emphasizing the decision steps to be implemented.

5.3 SMART RCM FRAMEWORK

As shown in figure 38, the DMD stores and makes available the information needed to be consumed by the decision models in the RCM steps. The Smart RCM framework proposed in Figure 42 presents these steps and the decision making processes. In the lower part of the figure is the DMD, already with the information structured to be used in each phase of the deployment, according to the presented flow. Thus, the available information is used as inputs to decision processes (MCDMs), considering the preferences of decision makers.

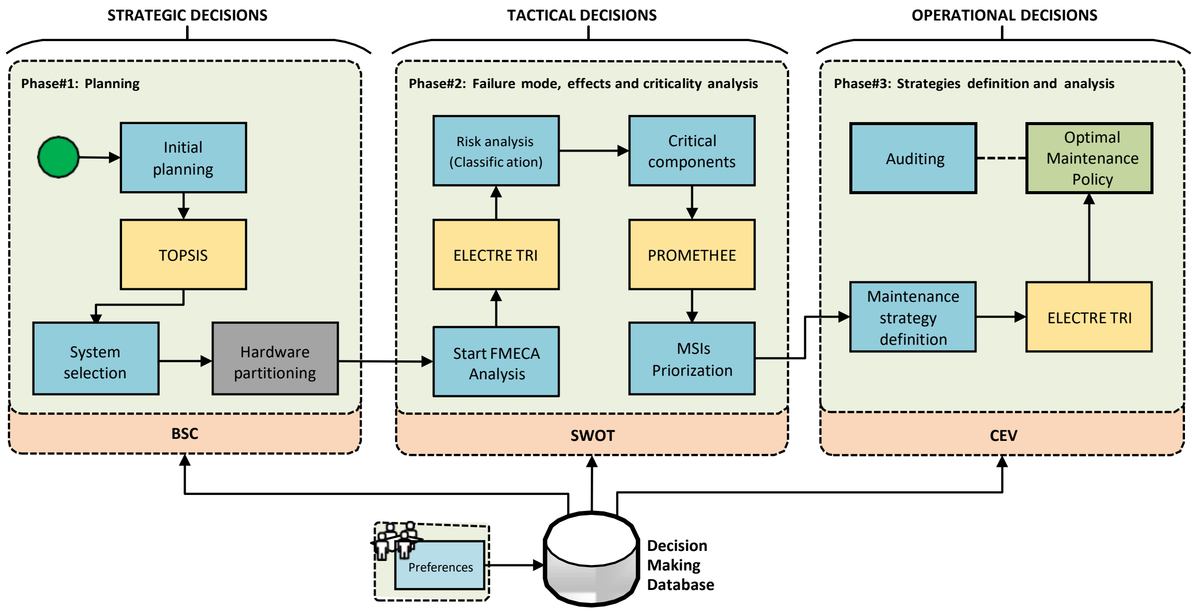


Figure 42. Smart RCM framework

The upper part of figure 42 shows an organizational layering (strategic, tactical, and operational) that defines the level of analysis for that phase. Phase 1 (Planning) performs management-level decisions, requiring top-tier metrics and information. Phase 2 (FMECA) conducts risk analysis, using information at a tactical level, with a multidisciplinary bias. Finally, layer 3 (MSS) has predominance of execution information, present in the operational layer.

The central boxes represent the phases and tasks to be performed in Smart RCM, according to their execution flow. These tasks are allocated according to the necessary actions presented in the RCM conceptual model (Figure 36), and are supported by their respective decision methods.

The lower part of the blocks of the deployment phases presents the filters used to form the structural basis of the indicators used in each decision model. In the first phase, the BSC methodology provides subsidies for better organization of the indicators for selection of the passive application systems of RCM. In phase 2, the SWOT methodology assures the selection of the best metrics in the classification and prioritization of the system items, improving the overall system vision under internal and external aspects of the company, analyzing efficiently its criticality indexes. In phase 3 is proposed a new approach called CEV (Criticality, Efficiency and Viability), which organizes the indicators to select the maintenance tasks under these three perspectives, providing a general and systemic view of the metrics that are in fact important for the taking necessary decisions.

Under aspects of database, the quantitative information should be subject to sporadic reviews according to the audit program present in phase 3. The quantitative information will be modified automatically as it is the process data with automatic updates. The quality of the information stored in the DMD is important to ensure the efficiency of the program, which must undergo audits at a frequency determined by the managers involved.

More details on the three phases of deployment are presented below.

5.3.1 Phase 1: Planning

At this stage the human resources structure and tools necessary for the development of the RCM program must be defined. In the sequence the activities must be initiated with the appropriate selection of the system to be analyzed, based on strategic indicators that are chosen by company direction (according to the process characteristics and level of maturity), defined in “Selection Step” of DMD development, according to Figure 42.

This early phase of Smart-RCM is best shown in Figure 43.

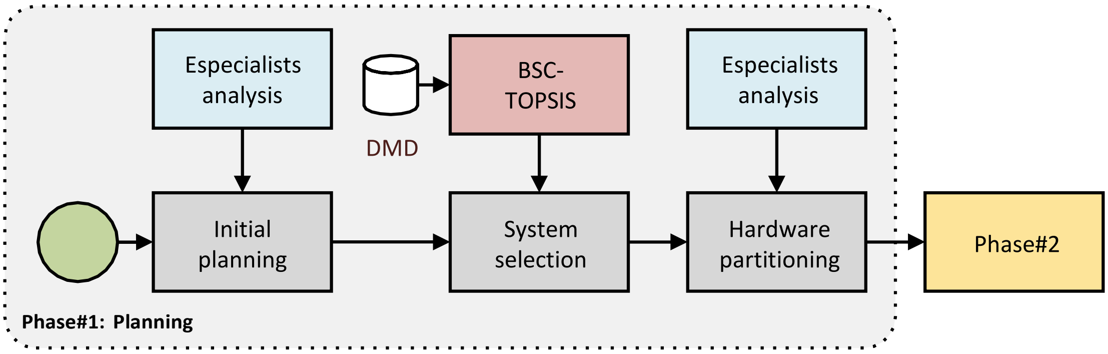


Figure 43. Planning phase from Smart-RCM framework

To support the selection of the most viable systems for the application of Smart-RCM, this research uses the BSC (Balanced Score-Card) tool, which consists of a strategic management model that helps to measure the progress of companies in their long-term objectives. The BSC was proposed by [114], and is considered a model that translates the mission and strategy of a business into a set of quantifiable objectives and measures.

The measures are built on the views of the investor (financial perspective), performance attributes of customer value as well as the long and short term objectives (perspective of the internal process) and finally, development and learning value (learning perspectives and growth) [115].

In order to measure each perspective, company managers should define which indicators should be used as decision criteria. For example, in the "Internal Business Process" perspective, process or equipment performance indicators can be selected. These indicators should be extracted from the base generated by the DMD (See topic 6.3). Figure 44 represents the dimensions around BSC.

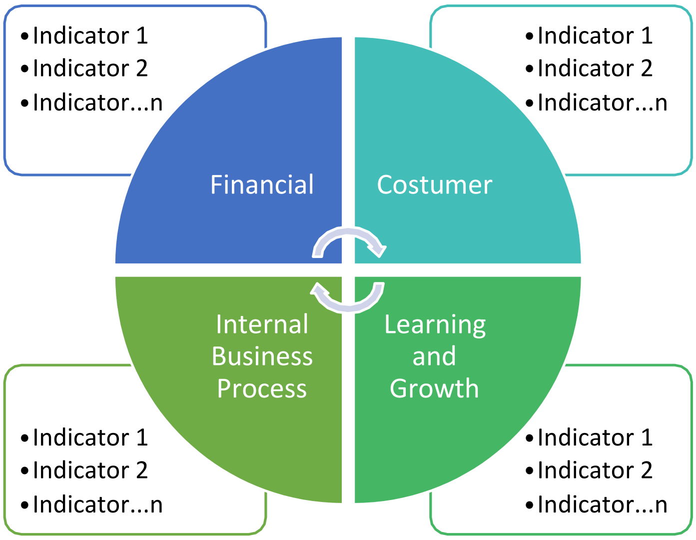


Figure 44. BSC model to support the system selection

Thus, in this first phase of Smart-RCM the indicators of the BSC dimensions will be criteria used in the multicriteria decision model. In this case, the TOPSIS method will be used, which evaluates the performance of the alternatives through its similarity with an ideal solution. According to this technique, the best alternative is the one closest to the ideal solution and the farthest from the non-ideal solution. Figure 45 shows the matrix of the TOPSIS model to select the most viable systems for the application of Smart-RCM, showing the criteria (indicators) under the BSC perspective and the alternatives (systems).

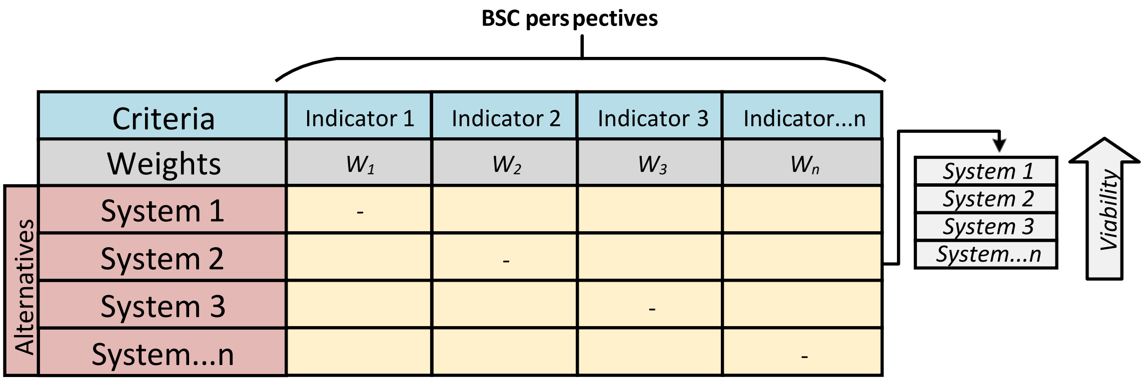


Figure 45. TOPSIS generic matrix for system selection

Plants have several systems, and each system has a certain degree of importance to the business process. Thus, the present research highlights the importance of the correct selection of the systems for the implementation of the RCM, proposing the use of MCDM technique using criteria from DMD to select the most critical system to be analyzed.

After structuring the most critical systems it is possible to apply the RCM in that have been defined as priority. The RCM team should define if one or more systems should be analyzed, since the RCM program needs resources (people and infrastructure), resulting in additional costs that must be evaluated. It is recommended the first application in a single system for maturing the methodology by the team responsible for the implementation, as well as the managers of the company.

The fact is that, according to [116], deciding at which level the analysis should be conducted is a difficult task. It is often necessary to make adaptations, since the workload can be high even for a moderately sized system. However, it is a general rule to expand the analysis to a level at which estimates of the failure rate are available or obtainable.

Once the system has been chosen, a hierarchical structure must be constructed, partitioning the hardware into equipment and components. The information of the equipment must be created up to the level component to be used in the next phase. The operational context and boundaries of the system selected for analysis should be mapped. Process data, flowcharts, procedures and technical content could support this phase. Figure 46, adapted from [116], represents the structure of a plant, with hierarchical levels.

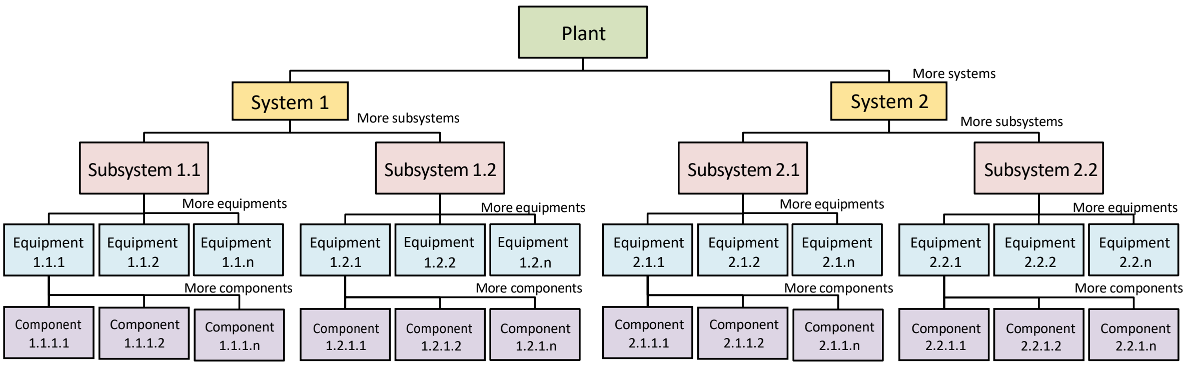


Figure 46. Plant partitioning

Software and hardware maintenance items are selected from a plant decomposition into systems, subsystems, equipment, and components [116]. In the present research it is suggested an analysis at equipment level, since from this layer the indicators are commonly available and easy to obtain. The lower the level of analysis, the more difficult is access to information. However, this selection can be made at the time of deployment.

The output of this first phase will be a ranking of the most viable systems for Smart-RCM. The second phase carries out the survey of the Maintenance Significant Items (MSIs) using FMECA analysis, through its classification and ranking of the system items, according to the level of analysis.

5.3.2 Phase 2: Failures modes, effects and criticality analysis

Traditional FMECA approaches apply the Criticality Analyses of failure modes are based on the three risk parameters of severity (S), occurrence (O) and detection (D) whose product returns the risk priority number (RPN). Despite its wide use, the classical RPN has been widely criticized for having many shortcomings [117]. As a result, numerous enhanced versions of the traditional FMECA have been applied and the Smart RCM proposed in present research is one of them. The FMECA model to be implemented is based on SAE RCM standards - for more details, see [25,26].

This phase is basically the application of FMECA, with qualitative and quantitative approach (data from DMD). The collection of information should be registered in a spreadsheet that will ensure the documentation of the failure modes associated with each functional failure, its causes and effects, assisting in the analysis of maintenance actions. The application of MCDM techniques is employed to classify and prioritize the failure modes based on criticality analysis.

This information from DMD is used as inputs to the MCDMs, as shown in Figure 47.

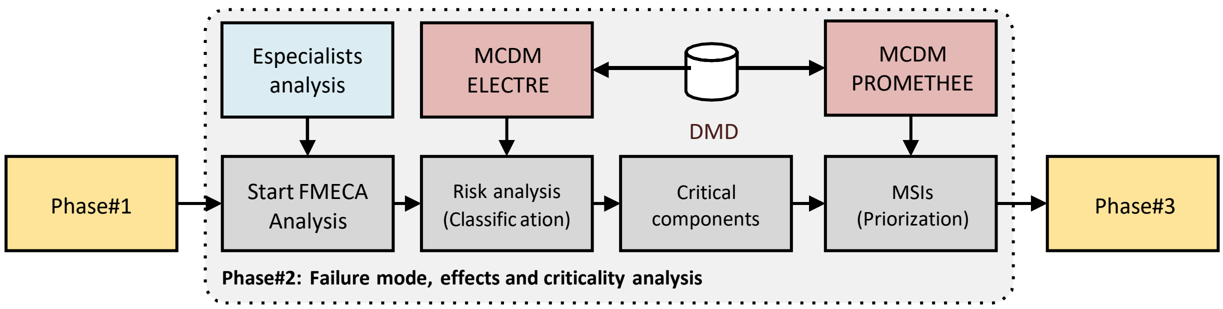


Figure 47. FMECA phase from Smart-RCM framework

This phase has two main objectives: (i) to classify system components (MSIs) into criticality groups and (ii) prioritize these items for subsequent strategic maintenance actions. These steps are explained below.

Risk analysis – classification

This decisional step consists in using the ELECTRE TRI method to classify the equipment / components through risk analysis. The tool used to formalize this stage is the FMECA, which develops the analysis of failure modes, the effects of failure on the system functions and their criticality. Figure 48 presents the ELECTRE structure.

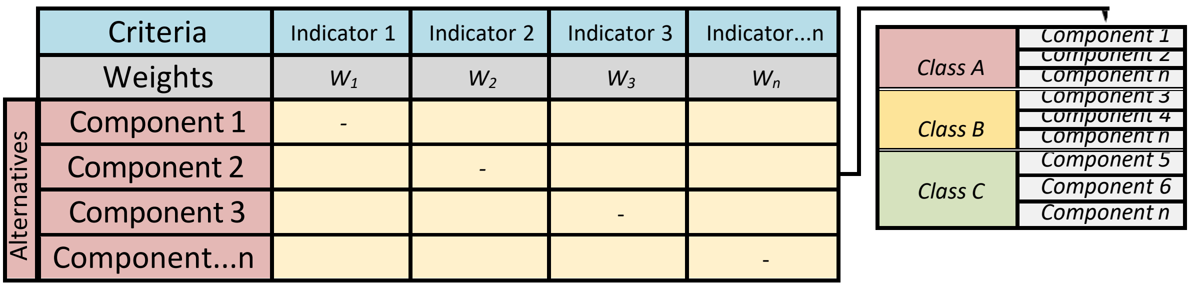


Figure 48. ELECTRE structure to risk classification

Groups are formed using levels of criticality A, B and C, being A items of high criticality, B of medium criticality and C of low criticality. This classification supports the maintenance strategies to be adopted in phase 3 of Smart-RCM.

MSIs priorization

This step prioritizes the most significant items in relation to their criticality indexes to the system. A ranking is performed and serves as the basis for step 3 for choosing more critical maintenance strategies for the most critical items. Because it is a dynamic model, this list is updated according to the information of the indicators requested in the DMD.

This information feeds the PROMETHEE model, which dynamically outputs the list of items and their criticalities, supporting MCDM inputs from phase 3, which selects maintenance strategies according to criticality levels. The structure of the method (PROMETHEE) is presented in Figure 49.

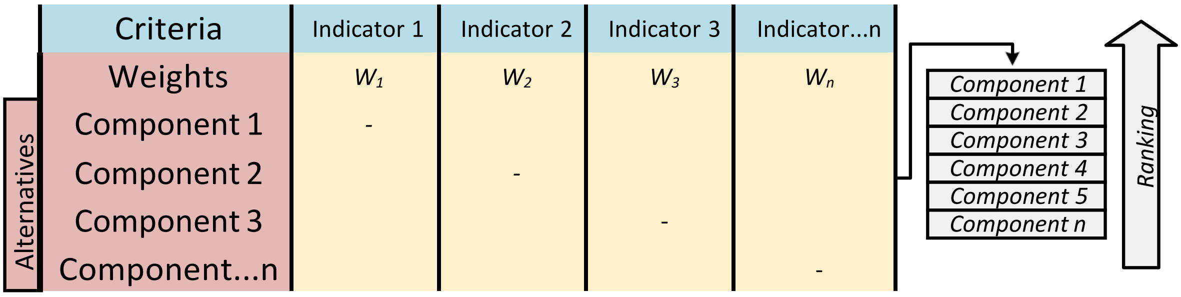


Figure 49. PROMETHEE structure for criticality ranking

With the robustly classified and ranked items, the maintenance strategies can be better selected, according to the methodology presented in the following topic (phase 3 from Smart-RCM framework).

5.3.3 Phase 3: Strategies definition and analysis

This phase addresses many of the issues considered prior to implementing an RCM program, in a knowledge and decision context. Applying the adequate techniques, the selected tasks are improved and updated to maintenance plan. As the level of maintenance maturity increases, tasks selected previously can be changed to a most adequate type (for example, a task in a failure mode characterized like RM (Reactive Maintenance) can be changed to TbM (Time-based Maintenance). The strategies adopted in maintenance plan have to be analyzed continuously. The results tracking has to be formalized with a readable format and feedback the RCM program.

The literature has several approaches to maintenance policies. In the present research, it is proposed a selection of the tasks at a higher level, with alternatives of using techniques of (i) RM (Reactive Maintenance), (ii) TbM (Time-based Maintenance), (iii) CbM (Condition-based Maintenance) and (iv) PRx (Prescriptive Maintenance [adapted from 119]. Under each of the four "umbrellas" we have specific tasks, according to the structure of each company / maintenance sector. In this case, the choice is linked to the maintenance planning team, who must define the specificities of each work-order.

More critical equipment / machines should be considered with the application of prescriptive maintenance techniques (including Engineering activities to adapt the technologies); intermediate with time-based maintenance and condition-based maintenance and the least critical with reactive maintenance (Run-to-failure).

Based on the criticality of each item listed in the previous phase of the Smart-RCM, they undergo a decision process also through the application of multicriteria method. This analysis will define which maintenance policy is feasible for each item. Figure 50 presents the steps of phase 3.

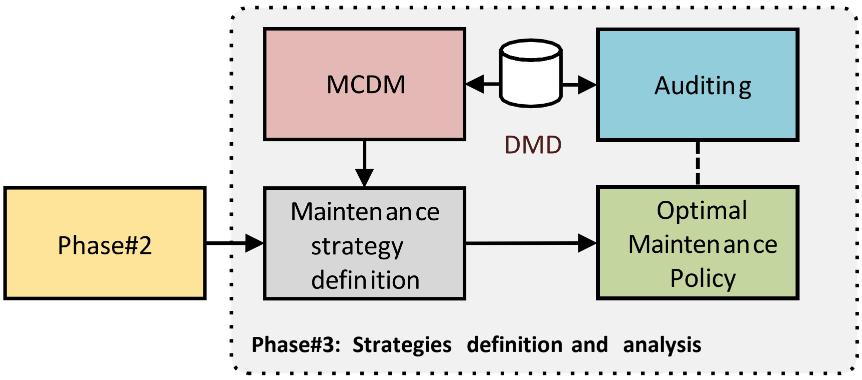


Figure 50. Strategies definition and analysis phase from Smart-RCM framework

As a criterion for the selection of maintenance policies, a new approach is proposed, in which the maintenance strategy is at the ideal point in the intersection between Criticality, Efficiency and Viability (CEV). Figure 51 presents this conception with the three perspectives and the Sweet Spot called MSS (Maintenance Strategy Selection).

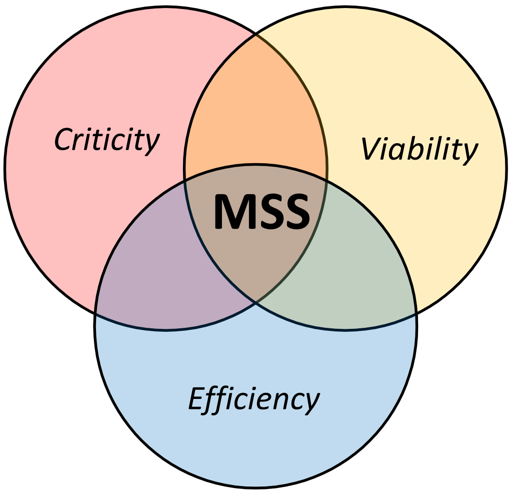


Figure 51. Perspectives for the MSS Sweet Spot

The CEV perspectives are better explained below.

Criticality

Indicator collected in the previous phase of Smart-RCM, after the classification and prioritization of MSIs. This is a quantitative metric, extracted from the final ranking of the items in Promethee method.

Efficiency

It is proposed to extract the OEE (Overall Equipment Effectiveness) indicators of the item to be analyzed. It is the product between three indicators (OEE = Availability x Performance x Quality). These measures are quantitatively extracted from the company's information system. The calculations are presented below.

$$Availability = \frac{Capacity\ used}{Capacity\ available}$$

$$Performance = \frac{Ideal\ productive\ time}{Real\ productive\ time}$$

$$Quality = \frac{Quantity\ produced - Quantity\ reworked}{Quantity\ produced}$$

The indicators and the efficiency result of the equipment are calculated in percentage values. 85% efficiency is the current benchmarking in the WCM (World Class Manufacturing) scenario.

Viability

The application of a certain maintenance strategy should verify its feasibility of implementation and execution. In this context, it is proposed to use two metrics: (i) Maintainability and (ii) Costs. The standard BS EN15341:2007 [120] establishes groups of maintenance performance indicators that support this approach. Maintainability addresses technical maintenance issues and Cost refers to financial expenses with maintenance activities. The indicator Maintenance Costs is calculated by dividing Total Downtime by Number of Service Breaks. The indicator Maintainability is qualitative, having to be converted according to the values raised by the maintenance planning, which can assume values on a scale involving attributes of ease, accuracy, safety and economy in maintenance tasks.

The criteria are the CEV perspectives and the sub criteria are the indicators. Some indicators are still selected in the construction of the DMD, by the RCM group. As the objective of this phase is to classify the items for allocation in different maintenance strategies, the use of the Electre Tri method is proposed. The decision structure is shown in Figure 52.

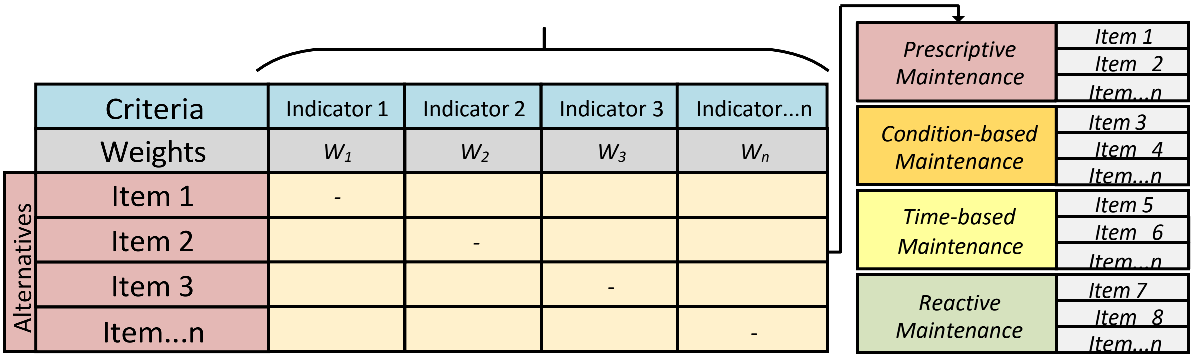


Figure 52. MCDM structure to maintenance strategy selection

In the implementation and in the improvements that must happen through the audit plan other indicators can be inserted, according to the need of the company. Therefore, all RCM processes must undergo a periodic review, both in the information used in decision-making and in the decisions themselves [25]. The process used in conducting the reviews should ensure that all RCM issues continue to be satisfactorily met. The asset management program, derived from RCM, is intended to ensure that the asset continues to meet the functional expectations of the moment for its owners and users.

It is important to note that the present work suggests the use of the indicators raised in the literature, however some specific information or measure can be inserted to optimize the model, such as new intelligent equipment, sensors and data sources included related to Industry 4.0. The flexibility of changing the parameters of the MCDMs allows the constant updating of the RCM.

5.3.4 Auditing Smart RCM

The presented framework consists of a database (DMD) that unites qualitative and quantitative information to be used in the Smart-RCM phases. This basis is the focus of the audit effort as it focuses on the indicators used in the RCM analysis, which serve as a basis for the implementation and evaluation of the program.

For the continuous evaluation and continuous improvement of the RCM, an audit program is proposed, being constructed with the following elements: (i) survey with general evaluation questions of the program and (ii) specific analyzes in the DMD indicators. Details are given below.

Survey for the general evaluation of RCM

The proposed survey consists of a specific questionnaire to be answered by the specialists, for an evaluation of the program under general aspects. The answers should be analyzed for possible modifications or adaptations in new opportunities for the development of the Smart-RCM framework. This questionnaire is based on the publications [34,38], being composed by basically two parts: (i) implementation checklist and (ii) results evaluation survey.

Specific analyzes in DMD indicators

Qualitative and quantitative metrics are components of the multicriteria decision models, for the choices of the best alternatives in their RCM scope. Qualitative measurements are inserted into these models through their conversions to quantitative scores (scales). These should be audited sporadically, since the nature of the information is more static than dynamic. They should take into account changes in company objectives, use of new techniques or technologies, changes in government laws, appropriateness of standards, et. Quantitative metrics are originated from datalogs of the company's information systems, being dynamic information. This information is updated according to the potentiality of the system used and the need assessed by the specialists.

Idle machine time, failure rate, operational stops, etc., are examples of these metrics. Changes may occur due to the insertion of new technologies, installations of new measuring points, changes in projects, changes in the life cycle of the equipment, etc. The indicators used can be altered for better interpretation and RCM analysis, through a review of the DMD, whose sporadic nature should also be analyzed by the group of specialists.

The conceptual basis for these approaches is presented in Table 5.

Table 5. Audit Plan information sources

Action	Source
Analysis of the answers to the basic questions of the RCM	RCM II – Moubray [15]
RCM assessment forms (from the literature)	SAE JA1011 [25], Nasa [31]
Query indicators (updates)	Systematic Literature Review
Proposals for improvements (sensing, standards, policies, etc.)	Industry 4.0 - Publications
Analysis of performance indicators	EN 15341 [120]
Procedures Writing and RCM Manual	Internal work
Trainings, updates	Internal work

With the results of the application it is possible to locate gaps in its functions, organizational and technological. These can be analyzed according to the experts of human resources, and directed outwards as action plans for improvements.

The results obtained after the application of the dynamic decision making techniques have the purpose of ordering the machines of the system by means of the quali-quanti information, with the indicators and their preference values (weights) extracted by means of peer reviews. For the identification and evaluation of possible uncertainties in these processes, it is important in the evaluation of the Smart RCM the application of sensitivity analyzes, which can determine the robustness of the solutions obtained in the decisions. This analysis allows the prediction of the result generated by changes in the parameters (indicators) or in the activities (selection of the system, risk analysis and selection of maintenance strategies) in the MCDMs models of the Smart-RCM phases.

These analyzes may determine how the course of the solutions obtained with machine prioritization can be modified with changes in the variables of the decision-making process. When these changes occur, you can use the output information in the problem formulation step.

Through this analysis also known as "what-if" analysis, recommendations for decision-makers can be suggested based on the change of variables in the analytical model. As a hypothesis test, the goal is to test and quantify performance results through different ways to achieve the ultimate goal of the process.

The withdrawal or insertion of new indicators as well as changes in their weights must be analyzed and tested, generating suggestions for changes in the information available for the analyzed system. For example, in the stage of risk classification (phase 2 of Smart RCM) a machine considered non-critical (class C) can, after insertion of a new criterion (indicator) can have its position changed, being classified as critical (class A or B). Consequently, the maintenance policy to be adopted can be changed, for example, from corrective to predictive, due to the new classification of the machine as critical. It is an important approach and can bring questions about investments in new technologies, including better sensing of machines, which are commonly discussed around the concepts of Industry 4.0.

The process of continuous improvement is an already widespread practice in the area of industrial maintenance, whose objective is to analyze the tools and methodologies used for later re-adaptation.

5.3.5 Operational framework

In order to improve the interpretation of Smart RCM, Figure 53 presents the proposed model with an operational view. It is possible to observe the interconnection of the phases of the RCM methodology with the use of analytics tools. The mapping of indicators in literature provides a basis for initial metrics, which are selected by a group of experts and managers. With qualitative and quantitative characteristics, these indicators are filtered and organized to constitute the DMD, data source for the RCM stages. The treatment of this database is performed with process mining tools (quantitative indicators) and scales (qualitative).

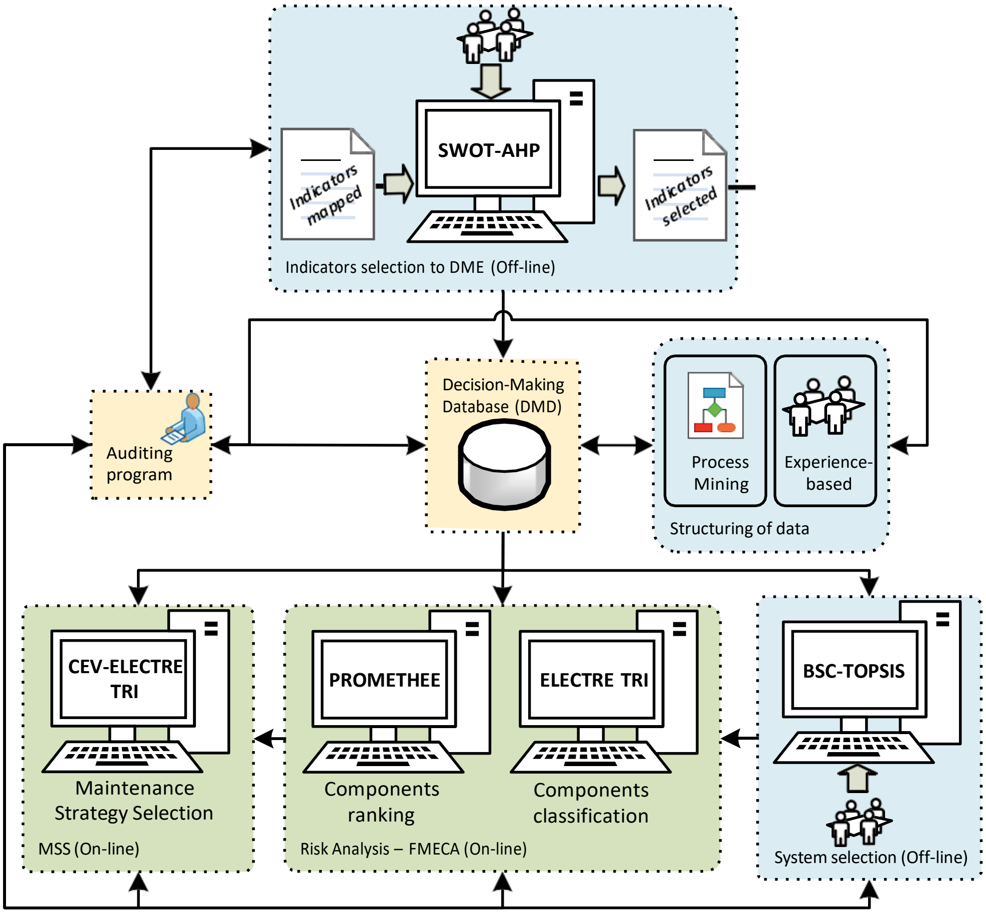


Figure 53. Operational view of Smart-RCM

MCDMs are used at all stages, with support of strategic management tools for better organization of information. The items of the installation of the machines and equipment are classified and ranked, for the prioritization in the maintenance planning. Most critical items are amenable to the use of more advanced maintenance strategies.

The selection stages of the indicators and the selection of the system to be implemented by RCM are offline, passive processes of changes with higher frequencies defined by the audit plan. The phases of classification and ranking of risks, as well as the selection of maintenance strategies, occur in real time, since the quantitative indicators are visited in the maintenance information system.

With the use of this qualitative basis in the decision-making tasks, the advances made are noticeable, and it exalts important and current concepts that permeate Industry 4.0.

5.4 DISCUSSIONS

It is commonly observed that maintenance professionals are combining quantitative and qualitative techniques in an effort to identify failure modes, investigate motives, and attempt to reduce downtime. However, the emergence of new connected technologies may allow the machines to perform these tasks, both maximizing the life of the machine components and avoiding machine failure. In this context, the proposed Smart-RCM develops techniques and methodologies for the constant flow of physical asset data, allowing agility in decision making. Unforeseen situations and changes in facilities conditions can be detected in real time, decreasing frequency or eliminating possible damage.

Proper structuring and use of company data can enable end-to-end transparency, and proper choice of algorithms and analyzes for the interpretation of such data can allow for holistic decision making on asset maintenance approaches.

The combination of the tools and technologies that make up the Smart-RCM allows the selection and treatment of company data, making important information available to many decision makers in order to increase the reliability of the systems. In this proposal, the creation of DMD based on information of RCM applications in several industrial segments allied to the management of assets brings a new approach, with characteristics coming from Industry 4.0. The use of analytics tools with support of strategic management tools, MCDMs and Process Mining methods highlight the potentiality of the proposed system, which aims at the dynamism of decision-making in the Smart-RCM environment.

Nowadays, the concepts of Industry 4.0 have been developing concepts that exalt the term "Smart", in order to obtain information, interpret them and make quick and accurate decisions, in real time. In this context, the maintenance function seeks to identify sources of potential failures by taking action before they occur.

Thus, the concept of Smart-RCM is linked to industry 4.0 due to the use of its technologies, since the latter is a term coined by the high-tech strategic design of several renowned institutions to designate the computerization of manufacturing. This makes it easier to see and run smart factories, which do not just depend on people to make decisions.

Currently, few humans are seen on assembly lines, and these supervise the work of machines through software integrating technology into automation and information technology. The storage of data, hardware, software and networks are much more effective in the industry 4.0, being technically and economically possible to integrate information technology functionalities into more devices, and consequently to achieve more significant results.

Thus, the Smart-RCM framework integrates the design of intelligent plants, which collect, store and analyze data to make decisions in real time.

6 SMART RCM APPLICATION IN SIMULATED ENVIRONMENT

In an industrial process, it is commonly performed the decomposition of the company's production process into various manufacturing steps, which are executed in your workflow. Therefore, in order to interpret and optimize a process, which should soften and / or solve problems, especially at the level of production, execution and coordination of various workflows of manufacturing process, plays an important and indispensable role [121]. According to [122] engineering systems fit into a very broad area that involves multiple activities, such as engineering requirements, designs and specifications, implementations, tests and deployments. The biggest challenge is the lack of determinism, depending on the different paths that a process can take.

[123] elevate the importance of workflow management systems in today's competitive market by providing support for important decisions. However, in order for the system to be able to conduct some evaluations, it is necessary to use formalism requirements in the construction of the models, which significantly reduces the risk of erroneous decisions in relation to the project of the analyzed process. Scenarios can be performed immediately for discussion and analysis. According to [124], Petri nets have been extensively studied and applied successfully in the area of dynamic systems of discrete events, which are characterized by parallelism and synchronization. The incentives that lead to research in this area are the strong mathematical foundation and the availability of analysis tools [124].

Thus, for the Smart-RCM analysis a simulated environment is used. It is a production system modeled in Petri net proposed by [125]. With the parameterization of the model and the extraction of the datalogs tests in the system can be realized. Process mining techniques support the treatment of data extracted from the model to verify the proposed dynamic model. The process, techniques and tools used and the results will be presented below.

6.1 APPLICATION SCENARIO

In order to verify the viability of Smart-RCM, an intervention in a generic manufacturing process is proposed [125]. It consists of a model with manufacturing parameters and indicator measurements. The manufacturing process of a given product receives a configurable production schedule, executes service orders, and generates event logs for evaluation.

Issues related to operational and fault stoppages (inactive machine), scheduled and unscheduled, are measured. In addition, the verification of resources and transport, withdrawal and inspection of the product is carried out. Figure 54 shows a flowchart of the process, with its tasks and sub processes.

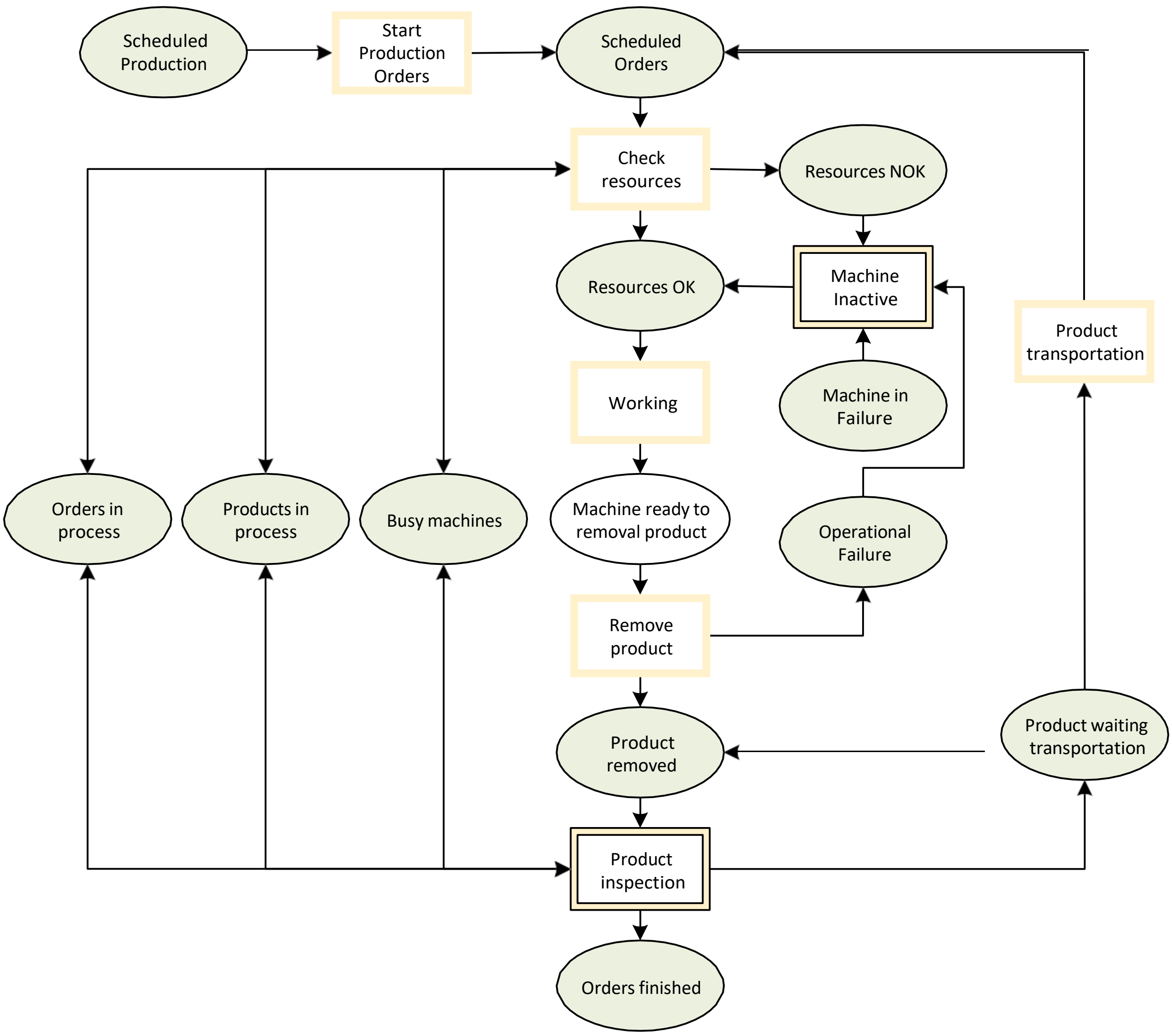


Figure 54. The process flowchart for the simulated environment

The process was developed in specific software for modeling and simulation of Colored Petri Nets - CPN Tools. It consists of a tool to edit, simulate and analyze high-level Petri nets with support for basic, timed and colored petri nets. It also performs simulations and has a space-state analysis tool.

The process was simulated to meet an initial Smart RCM analysis. Since the log does not record the information of the resources (production), the simulations were performed individually, simulating a process with machines operations in parallel, for the production of an "X" product. According to [25,116], the RCM analysis assesses failures under several levels: system level, sub-systems, equipment and components. Figure 46, presented on 5.3.1, represents the structure of a plant, with these hierarchical levels. However, the simulated environment used for this experimental application provides machine data records. This approach does not compromise the quality of the results, as the objective is to test the tools and dynamics of the Smart-RCM, regardless of the level of analysis used. Thus, ten simulations were performed (10 machines), each producing 200 pieces. Figure 55 presents the machines arrangement.

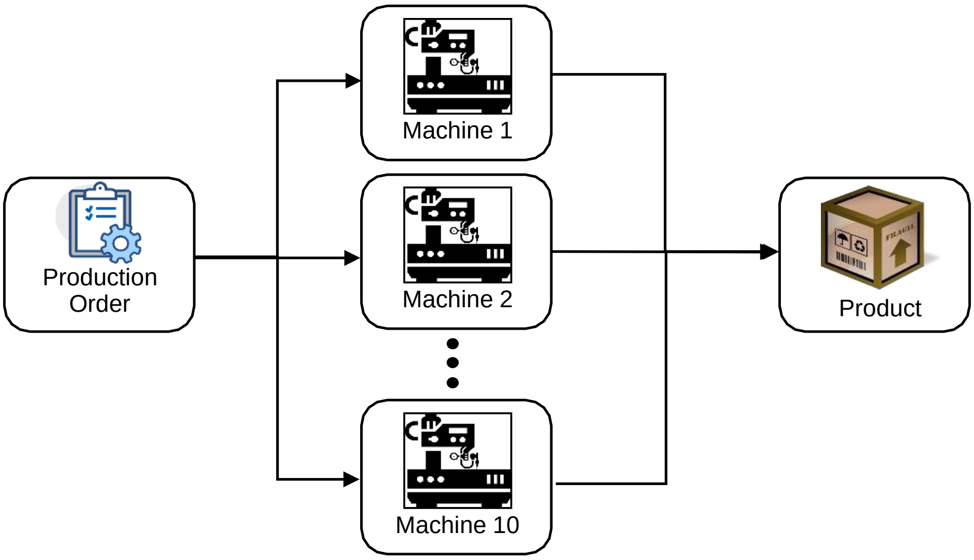


Figure 55. Layout of the simulated production system

The simulation was run sequentially in the CPN Tools software and the instances were generated in unique files for each simulation. The purpose of using CPN Tools with such a simulated environment is to generate datalogs for application in Smart-RCM. Each machine generated 200 log files with the extension "cpnxml". Using a conversion software (Prom Import) the 20 files were converted to a single with the extension ".mxml".

Thus, this procedure was repeated for the 10 machines, generating instances in single files for each simulation, which were used for the Process Mining in the Prom software. The next topics present the initial analyzes performed. Mining techniques are used to extract the quantitative data to analyzes of the decisional processes.

It should be noted that, at first, the simulation was performed using data and random choices, through the researcher's intuition and random data calculated by Excel.

6.2 DEPLOYMENT OF SMART RCM

In the following topics the three phases of Smart-RCM are presented through an application in a simulated environment.

6.2.1 System Selection – BSC-TOPSIS approach

As noted in previous sections, the RCM process is honorable and demands time and resources of the company. Thus, for the prioritization of the systems to be submitted to this process a multicriteria decision analysis is proposed. The method used is TOPSIS, with a criteria approach supported by the BSC strategic planning tool.

Initially the decision matrix is constructed with the structure presented in Figure 56. The alternatives are the systems available for evaluation and the criteria are the elements of the proposed BSC approach.

	BSC perspectives							
	Financial		Costumer		Internal Business Process		Learning and Growth	
	Maintenance Cost	Eonomic cost risk	Production cost	OEE	Failure rate	Availability	Safety Risk	Severity Rating
Weight	0,125	0,125	0,125	0,125	0,125	0,125	0,125	0,125
System A	5,000	1,000	5,000	72,000	0,031	84,973	4,000	1,000
System B	3,000	5,000	2,000	67,000	0,029	85,490	5,000	3,000
System C	5,000	2,000	3,000	88,000	0,058	75,262	2,000	1,000
System D	2,000	4,000	4,000	91,000	0,058	75,099	2,000	5,000
System E	1,000	3,000	3,000	85,000	0,030	85,329	2,000	3,000
	8,000	7,416	7,937	181,447	0,097	181,973	7,280	6,708

Figure 56. TOPSIS Decision Matrix

The qualitative indicators use a 5-point scale filled out by random values calculated by Excel and the quantitative indicators are extracted from the database of the simulated process model.

In the sequence, the normalized matrix of the method, shown in Figure 57, is constructed.

	BSC perspectives							
	Financial		Costumer		Internal Business Process		Learning and Growth	
	Maintenance Cost	Eonomic cost risk	Production cost	OEE	Failure rate	Availability	Safety Risk	Severity Rating
Weight	0,125	0,125	0,125	0,125	0,125	0,125	0,125	0,125
System A	0,625	0,135	0,630	0,397	0,319	0,467	0,549	0,149
System B	0,375	0,674	0,252	0,369	0,299	0,470	0,687	0,447
System C	0,625	0,270	0,378	0,485	0,597	0,414	0,275	0,149
System D	0,250	0,539	0,504	0,502	0,597	0,413	0,275	0,745
System E	0,125	0,405	0,378	0,468	0,309	0,469	0,275	0,447

Figure 57. Normalized Decision Matrix

The weights were, at first, filled with the same value, a result of the division between the eight criteria. The next step is the calculation and completion of the weighted decision matrix and the worst and best values, as shown in Figure 58.

	BSC perspectives							
	Financial		Costumer		Internal Business Process		Learning and Growth	
	Maintenance Cost	Eonomic cost risk	Production cost	OEE	Failure rate	Availability	Safety Risk	Severity Rating
Weight	0,125	0,125	0,125	0,125	0,125	0,125	0,125	0,125
System A	0,078	0,017	0,079	0,050	0,040	0,058	0,069	0,019
System B	0,047	0,084	0,031	0,046	0,037	0,059	0,086	0,056
System C	0,078	0,034	0,047	0,061	0,075	0,052	0,034	0,019
System D	0,031	0,067	0,063	0,063	0,075	0,052	0,034	0,093
System E	0,016	0,051	0,047	0,059	0,039	0,059	0,034	0,056
	V_j^+ 0,016	0,017	0,031	0,063	0,037	0,059	0,034	0,019
	V_j^- 0,078	0,084	0,079	0,046	0,075	0,052	0,086	0,093

Figure 58. Weighted Normalized Decision Matrix

In the sequence, the Euclidean distance from ideal and worst are calculated, which are the basis for the calculation of performance score. Thus, we have the final ranking (Figure 59) of the evaluation, with the selection of "System E" as a priority for the implementation of RCM.

	S_i^+	S_i^-	$S_i^+ + S_i^-$	P_i	Rank
System A	0,087	0,138	0,225	0,615	3
System B	0,099	0,122	0,221	0,552	4
System C	0,077	0,134	0,210	0,635	2
System D	0,104	0,119	0,223	0,535	5
System E	0,053	0,102	0,155	0,660	1

Figure 59. Final TOPSIS ranking

It is important to note that more systems can be analyzed as long as the company has a material and human resources structure for these simultaneous applications.

With the system selected for RCM implementation, the next action is the evaluation and selection of the qualitative and quantitative indicators that will be used in the other steps.

6.2.2 Assessment and selection of indicators - SWOT-AHP approach

According to [126], in some critical situations, it is not possible for a single expert to consider all relevant aspects of a problem. Thus, a multidisciplinary team was formed responsible for the analysis of the indicators. This team is composed of specialists laboring in a Latin American pulp and paper industry. More specifically, decision makers labor directly in the following sectors: (i) maintenance; (ii) production; (iii) occupational safety and health and (iv) quality control. The expert group consists of 4 maintenance analysts, 2 senior machine operators, 1 safety and environmental analyst and 1 process and quality manager.

Due to the intrinsic characteristics of the group decision making process, when involving more than one individual with their different views and values, it is important that the decision making process is well structured for effective decision making. For the criteria and alternatives to be well presented, a training was conducted with the presentation of the methodology and the AHP software. The general operational context of the plant was discussed and the present approach was presented. Figure 60 presents the flow of activities developed in this practical experiment.

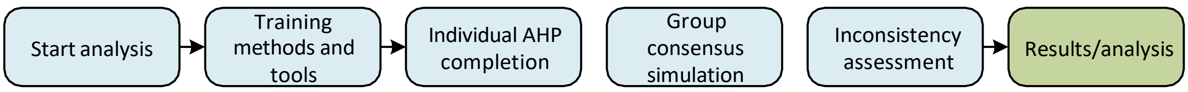


Figure 60: Application flow of SWOT-AHP method

To assess and select the indicators to be used in risk analysis, a AHP structure was constructed with the criteria based on the classic RCM approach and ISO 55000 (Asset Management), according to Table 3, under the perspective of the SWOT analysis. The structure is shown in Figure 61.

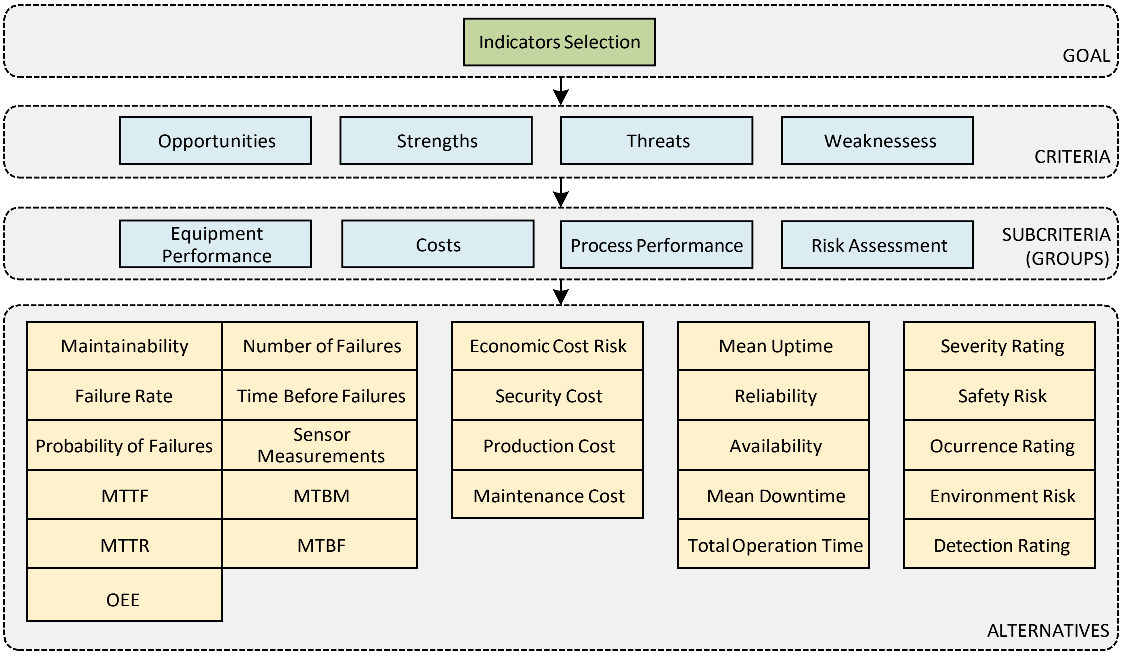


Figure 61. AHP structure for SWOT-AHP to priorization of indicators

The group consensus was simulated according to the geometric mean of the individual judgments. The priority vector of the elements in the AHP analysis can be calculated using the average of normalized values, according to [127]. The responses were processed by a specific AHP software. Figure 62 presents the results, with the ranking of the indicators and their respective idealized and normalized values.

Rank	Indicator	Idealized	Normalized
1	OEE	0,8066	0,1831
2	Safety Risk	0,7992	0,2780
3	Severity Rating	0,7889	0,2744
4	MTBF	0,7400	0,1680
5	Production Cost	0,7328	0,3427
6	Availability	0,6404	0,2624
7	Failure Rate	0,6023	0,1367
8	Security Cost	0,4944	0,2312
9	Economic Cost Risk	0,4896	0,2290
10	Reliability	0,4836	0,1981
11	Total Operation Time	0,4117	0,1687
12	Ocurrence Rating	0,3969	0,1381
13	Probability of Failures	0,3839	0,0871
14	Detection Rating	0,3558	0,1238
15	Number of Failures	0,3345	0,0759
16	Mean Downtime	0,3104	0,1271
17	MTTR	0,3096	0,0703
18	MTTF	0,2960	0,0672
19	Environment Risk	0,2868	0,0998
20	Maintenance Cost	0,2344	0,1096
21	Mean Uptime	0,2301	0,0943
22	Sensor Measurements	0,2154	0,0489
23	Maintainability	0,1556	0,0353
24	Time Before Failures	0,1385	0,0314
25	MTBM	0,1308	0,0297

Figure 62. Results of priorization of indicators from SWOT-AHP approach

In case the consistency index proves to be unsatisfactory, comparisons regarding this matrix should be reviewed again. The inconsistencies of the analyzes performed were calculated and are presented organized in four perspectives (indicators grouping of Figure 33). The relationship between the inconsistency values for the indicator groups and the decision makers is presented in Table 6.

Table 6: Inconsistency values for indicator groups and each decision maker

Decision maker	Equipment Performance	Process Performance	Risk Assessment	Costs
#1	0,0797	0,0911	0,0533	0,0806
#2	0,0932	0,0885	0,0735	0,0909
#3	0,0751	0,0323	0,0374	0,0742
#4	0,0927	0,0479	0,0780	0,0813
#5	0,0807	0,0427	0,0320	0,0598
#6	0,0317	0,0779	0,0516	0,0442
#7	0,0970	0,0653	0,0847	0,0454
#8	0,0802	0,0597	0,0416	0,0536

When considering the intrinsic difficulties of the human being to make decisions in the face of many information and multiple criteria problems, a tolerance of 10% can be admitted [128]. As shown in Table 5, no decision maker exceeded this limit, which satisfies the application of the method.

For prioritization of indicators, those involved with the analysis may suggest some criteria for selecting a specific quantity for later use in the RCM program, or even choosing to use all together. In this application, the group decided to use the classic rule 80-20 (Pareto chart), and a cut line was drawn in the list of indicators. Thus, eight indicators were extracted for the analysis of risks: (i) OEE, (ii) Safety Risk, (iii) Severity Rating, (iv) MTBF, (v) Production Cost, (vi) Availability, (vii) Failure Rate and (viii) Security Cost. The results are shown in Figure 63.

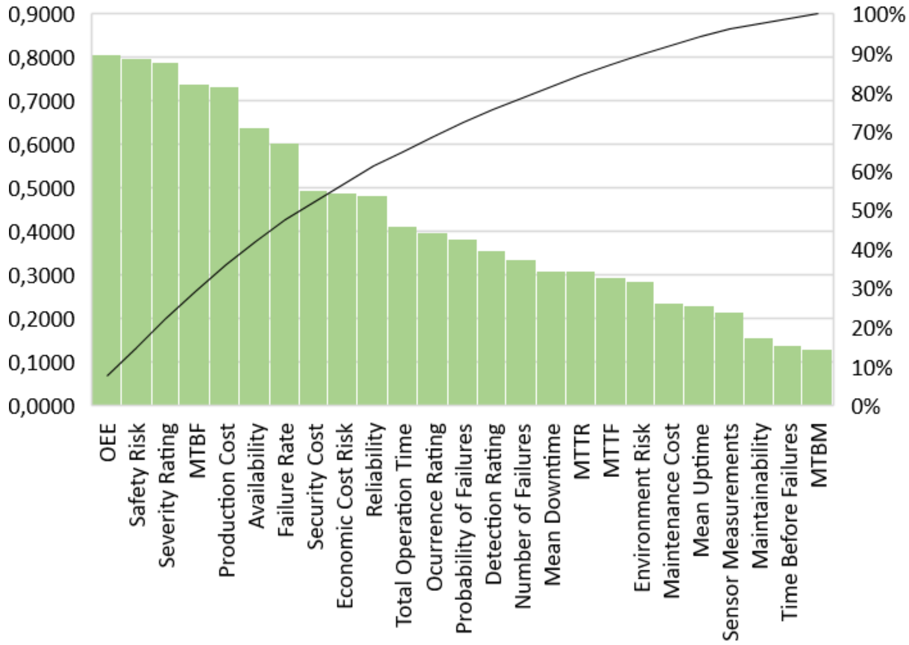


Figure 63. Cutting line for selection of indicators

This phase brings results that should match the reality of the company. In this specific case, it is clear that most of the selected indicators are classic, common in RCM applications, but others are specific. Compared to the results obtained from the mapping results of the indicators in the literature (Figure 31), Figure 64 is presented. In it we have a relationship between the indicators selected by the experts and the amount of citations extracted in the study presented in Topic 4.

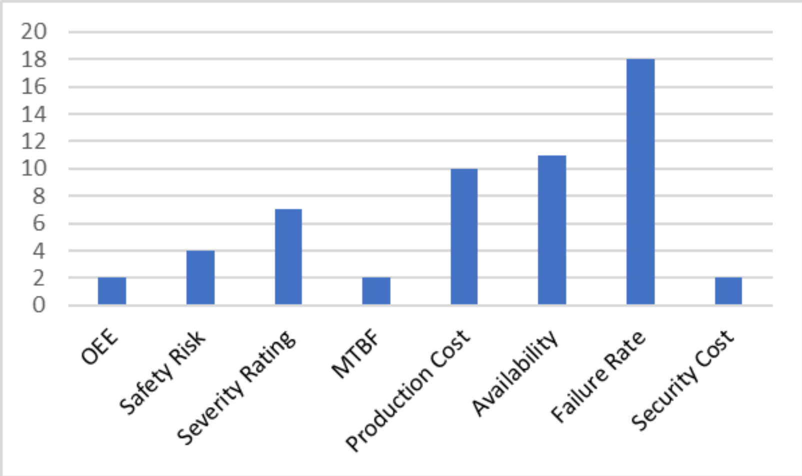


Figure 64. Number of researches using the selected indicators

Classic indicators in RCM applications such as Availability and Failure Rate are widely used and cited. Others, such as OEE and Security Cost are used in a few applications. Analyzing the indicators selected by the evaluation team, some considerations are raised, presented on Table 7.

Table 7. Considerations about indicators selected

Indicator	Considerations
OEE	Indicator not commonly found in RCM, but important in modern approaches such as this research, as it encompasses important data and in line with ISO55000, which deals with asset management.
Safety Risk	Indicator little found in the literature researches, but classic in RCM, including in RAMS (Reliability, Availability, Maintainability and Safety) approach.
Severity Rating	Used for RPN calculation, product among the indicators of occurrence, severity and detection - classic RCM approach.
MTBF	Although little mentioned directly in the research, this indicator supports the calculation of other indicators, such as Failure Rate, for example. It is an important parameter for the reliability of the system.
Production Cost	Indicator not used in classic RCM approaches, but important for the company. Found in contemporary approaches, it was selected by the team of decision makers because of the high cost of production of the company where they operate.
Availability	Widely found in RCM approaches, it measures whether the resource is committable, operable, or usable upon demand to perform its designated or required function. It directly impacts other indicators such as reliability, maintainability and security.
Failure Rate	Widely used in RCM, it is an easy indicator to extract from processes. It brings data related to the number of failures in a given time.
Security Cost	Little found in the literature and with little research that used this indicator. The experts understand how important for the company, because these costs are currently high, due to adjustments that have been implemented to comply with a Brazilian standard of safety in machinery and equipment.

Such considerations demonstrate the importance of this phase, as it prioritizes the most important indicators for the company's reality, taking into consideration specific aspects related to technology, structure, resources, goals, business objectives, among others.

With the indicators selected and ranked, the selected production system was simulated for the generation of event logs. The sequence for creating this database is shown in Figure 65.

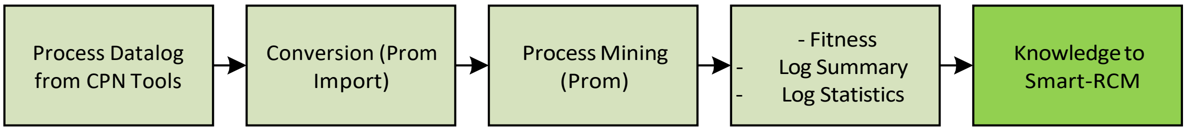


Figure 65. Process Mining flowchart

The extracted data (quantitative indicators) underwent a statistical analysis through the application of basic plug-ins of the mining software used. With this, the ranks were measured and analyzed, under aspects of quantity of measurements and calculations of times. Figure 66 presents the structure of the log summaries and Figure 67 presents the log statistics.

Model element	Event type	Occurrences (absolute)	Occurrences (relative)
Idle Machine	Complete	205	11,69%
Working	Start	205	11,69%
Working	Complete	205	11,69%
Waiting machine	Complete	201	11,47%
Remove product	Start	201	11,47%
Remove product	Complete	201	11,47%
Waiting machine	Start	200	11,41%
Part produced	Good part	200	11,41%
Operational stop	Start	62	3,54%
Operational stop	Complete	62	3,54%
Failure while working	Start	4	0,23%
Failure while working	Complete	4	0,23%
Setup	Start	1	0,06%
Setup	Complete	1	0,06%
Part produced	Rework	1	0,06%

Model element	Event type	Occurrences (absolute)	Occurrences (relative)
Idle Machine	Complete	207	11,66%
Working	Start	207	11,66%
Working	Complete	207	11,66%
Waiting machine	Complete	201	11,32%
Remove product	Start	201	11,32%
Remove product	Complete	201	11,32%
Waiting machine	Start	200	11,27%
Part produced	Good part	198	11,16%
Operational stop	Start	68	3,83%
Operational stop	Complete	68	3,83%
Failure while working	Start	6	0,34%
Failure while working	Complete	6	0,34%
Part produced	Scrap	2	0,11%
Setup	Start	1	0,06%
Setup	Complete	1	0,06%
Part produced	Rework	1	0,06%

Figure 66. Data log summary

MACHINE 01

Activity	Arithmetic Mean (in Minutes)	Geometric Mean	Sum (in Minutes)	Nº of Measurements
Waiting machine	102,8828	4931,8055	20679,4500	201,0000
Failure while working	3,5375	184,4661	14,1500	4,0000
Operational stop	0,7965	36,5090	49,3833	62,0000
Remove product	0,3299	18,1763	66,3000	201,0000
Setup	10,4333	626,0000	10,4333	1,0000
Working	0,1654	9,7960	33,9000	205,0000

MACHINE 02

Activity	Arithmetic Mean (in Minutes)	Geometric Mean	Sum (in Minutes)	Nº of Measurements
Waiting machine	104,4544	5055,4374	20995,3333	201,0000
Failure while working	3,9472	219,4843	23,6833	6,0000
Operational stop	0,8824	40,6183	60,0000	68,0000
Remove product	0,3235	17,9171	65,0167	201,0000
Setup	10,4333	626,0000	10,4333	1,0000
Working	0,0787	0,0000	16,3000	207,0000

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Figure 67. Data log statistics

The next step is criticality analysis. For the presented process model, the analysis occurs at the machine level. This phase consists of two stages: (i) classification of machines with criticality and (ii) criticality priorization.

The classification is categorized by the ABC method using the Electre Tri multicriteria decision-making method. After priorization is performed using the Promethee method. For the structuring of the data (metrics) used in the decisions, Figure 68 is presented. Six quantitative and two qualitative indicators were selected, structured and calculated based on the literature.

Indicator	Reference	Calculation	
OEE	[82] Fore and Mudavanhu (2011)	$OEE = Availability \times Performance \times Quality$	Quantitative (from datalog)
MTBF	[118] EN-15341 (2007)	$MTBF = \frac{Total\ Operation\ Time}{Number\ of\ Failures}$	
Availability	[118] EN-15341 (2007)	$A = \frac{Uptime}{Uptime + Downtime} \times 100$	
Failure Rate	[118] EN-15341 (2007)	$\lambda = \frac{1}{MTBF}$	
Production Cost	[124] Adapted from Nahmias and Olsen (2015)	$P_C = \frac{(Downtime \times Units\ produced) \times Average\ profit\ per\ unit}{Downtime}$	
Security Cost	[79] Adapted from Pourahmadi et al. (2017)	$S_C = \frac{Expected\ security\ cost}{OEE}$	
Safety Risk	[73] Tang et al. (2017)	Table Scores (Table 7)	Qualitative
Severity Rating	[72] Gupta and Mishra (2011)	Table Scores (Table 8)	

Figure 68. Structuring data of indicators for criticality analysis

Quantitative indicators are presented using their formulas and qualitative using scoring tables (Saaty scale), presented in Tables 8 [102] and 9 [75].

Table 8. Score for indicator "Safety risk"

Rating	Value	Safety risk
No risk	1	No/Slight injury
Minor	3	Minor injury
Moderate	5	Major Injury
Significant	5	Single fatality
High	7	Multiple fatalities
Intermediate Preferences	2,4,6,8	Compromise condition between two conditions

Table 9. Score for indicator “Severity Rating”

Ranking	Effect	Comment
1	None	Insignificant effect, corrected immediately by the maintenance.
3	Low	Minor effect, the component suffers to a gradual degradation case if not repaired.
5	Moderate	Moderate effect, the component does not execute its function, but the maintenance of failure demands the stop of machine.
7	High	Critical effect, maintenance demands stop of machine.
9	Hazard	Very critical effect, failure brusquely interrupts the system functions.
2,4,6,8	Intermediate Preferences	Compromise condition between two conditions.

After the structuring of the information, the statistics of the process event logs were analyzed. The indicators were calculated using Excel, and the results presented in Figure 69.

	Machine #1	Machine #2	Machine #3	Machine #4	Machine #5	Machine #6	Machine #7	Machine #8	Machine #9	Machine #10
Statistics ↓	**Sum (in Minutes)**									
Waiting machine	20679,4500	20995,3333	25255,7667	30141,7500	20941,4667	23488,4167	30141,7500	23015,9167	23488,4167	21829,1833
Failure while working	14,1500	23,6833	12,7833	62,4000	28,5000	12,5333	62,4000	46,4000	12,5333	25,5000
Operational stop	49,3833	60,0000	57,9000	58,8167	60,0833	67,9000	58,8167	61,1667	67,9000	53,4333
Remove product	66,3000	65,0167	68,4167	63,8833	63,4333	68,1833	63,8833	65,8500	68,1833	68,0333
Setup	10,4333	10,4333	10,4333	10,4333	10,4333	10,4333	10,4333	10,4333	10,4333	10,4333
Working	33,9000	16,3000	51,6500	34,2667	16,8500	50,6333	34,2667	17,4667	50,6333	34,4667
Events ↓	**N.º of Measurements**									
Waiting machine	201,0000	201,0000	203,0000	200,0000	201,0000	201,0000	200,0000	201,0000	201,0000	203,0000
Failure while working	4,0000	6,0000	3,0000	8,0000	5,0000	2,0000	8,0000	10,0000	2,0000	4,0000
Operational stop	62,0000	68,0000	75,0000	67,0000	75,0000	75,0000	67,0000	73,0000	75,0000	69,0000
Remove product	201,0000	201,0000	203,0000	200,0000	201,0000	201,0000	200,0000	201,0000	201,0000	203,0000
Setup	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000
Working	205,0000	207,0000	206,0000	208,0000	206,0000	203,0000	208,0000	211,0000	203,0000	207,0000
Indicators ↓	**Quantitative Indicators Calculation**									
OEE	89,635	82,739	90,464	70,044	81,247	92,633	70,044	72,940	92,633	83,358
MTBF	40,004	25,292	62,800	20,925	30,160	98,575	20,925	15,492	98,575	41,592
Availability	91,876	86,500	93,646	72,846	84,105	94,023	72,846	76,952	94,023	86,710
Failure Rate	0,025	0,040	0,016	0,048	0,033	0,010	0,048	0,065	0,010	0,024
Production Cost	40,000	39,600	39,800	40,000	39,800	40,000	40,000	40,000	40,000	39,800
Security Cost	0,558	0,604	0,553	0,714	0,615	0,540	0,714	0,685	0,540	0,600
Safety Risk	8	1	9	3	1	3	4	6	7	8
Severity Rating	8	6	4	2	5	5	4	8	1	9

Figure 69. Calculations of quantitative indicators in Excel

6.2.3 Criticality Analysis - ABC Classification

With the indicators ready for the analysis of criticality, the decision model was created using the multicriteria tool Electre Tri, through Iris software. The "Action" column presents the alternatives (Machines 1 to 10). Each alternative has a lower and a higher category to which it can be assigned (ELow and EHigh columns, respectively).

Typically, the ELow column contains the lowest category (which is always 1) and the EHigh column contains the highest category (which defaults to 3). If you change these values, the assignment of the alternative is restricted: it becomes an example of assignment. Thus, all machines were assigned the same ELow and EHigh values. The following columns present the indicators (criteria) and their values for each alternative (machines).

The figure 70 presents the construction of the evaluation matrix.

Action	Elow	Ehigh	OEE	MTBF	Availability	Failure Rate	Production Cost	Security Cost	Safety Risk	Severity Risk
Machine 1	1	3	89,635	40,000	91,870	0,025	40,000	0,558	8	8
Machine 2	1	3	82,739	25,290	86,500	0,040	39,600	0,604	1	6
Machine 3	1	3	90,464	62,800	93,650	0,016	39,800	0,553	9	4
Machine 4	1	3	70,044	20,920	72,850	0,048	40,000	0,714	3	2
Machine 5	1	3	81,247	30,160	84,100	0,033	39,800	0,615	1	5
Machine 6	1	3	92,633	98,570	94,020	0,010	40,000	0,540	3	5
Machine 7	1	3	70,044	20,920	72,850	0,048	40,000	0,714	4	4
Machine 8	1	3	72,940	15,490	76,950	0,065	40,000	0,685	6	8
Machine 9	1	3	92,633	98,570	94,020	0,010	40,000	0,540	7	1
Machine 10	1	3	83,358	41,590	86,710	0,024	39,800	0,600	8	9

Figure 70. Evaluation matrix - Electre Tri

Figure 71 shows the calculated thresholds, that were defined with reference to the value of 1/3 of the range positive and negative. The weights were imported from the SWOT-AHP evaluation of the indicators evaluation stage. Figure 72 presents the upper and lower bounds of the cutting level (lambda) and the weights (ki refers to the weight of the i-th criterion).

	OEE	MTBF	Availability	Failure Rate	Production Cost	Security Cost	Safety Risk	Severity Risk
g(b1)	77,574	43,186	79,905	0,046	39,867	0,656	6,333	6,333
g(b2)	85,104	70,881	86,964	0,028	39,733	0,598	3,667	3,667
MAX/min	1	1	1	-1	-1	-1	-1	-1

Figure 71. Positive and negative thresholds for evaluation

	Lambda	k1	k2	k3	k4	k5	k6	k7	k8
LB-Lower	0,25	0	0	0	0	0	0	0	0
UB-Upper	1	0,144	0,132	0,114	0,107	0,131	0,088	0,143	0,141

Figure 72. Imports from the evaluation of indicators

With the parameterized software, the evaluation was performed, allocating the machines in critical classes (A, B and C). The results are shown in Figure 73.

↓ Classification	Machine #1	Machine #2	Machine #3	Machine #4	Machine #5	Machine #6	Machine #7	Machine #8	Machine #9	Machine #10
A								X		
B					X		X			X
C	X	X	X	X		X			X	

Figure 73. ABC classification of machines

In order to verify the behavior of the evaluation under changes in the indicators, two more indicators were incorporated, respecting the sequence evaluated previously. Thus, the "Reliability" and "Economic Cost Risk" indicators, both qualitative expressed in 5-point scale (Saaty) were randomly filled. Figure 74 shows the new evaluation matrix.

Action	Elow	Ehigh	OEE	MTBF	Availability	Failure Rate	Production Cost	Security Cost	Safety Risk	Severity Risk	Reliability	Economic Cost Risk
Machine 1	1	3	89,635	40,000	91,870	0,025	40,000	0,558	8	8	77,88	7
Machine 2	1	3	82,739	25,290	86,500	0,040	39,600	0,604	1	6	67,34	5
Machine 3	1	3	90,464	62,800	93,650	0,016	39,800	0,553	9	4	85,28	4
Machine 4	1	3	70,044	20,920	72,850	0,048	40,000	0,714	3	2	62,01	7
Machine 5	1	3	81,247	30,160	84,100	0,033	39,800	0,615	1	5	71,78	5
Machine 6	1	3	92,633	98,570	94,020	0,010	40,000	0,540	3	5	90,35	6
Machine 7	1	3	70,044	20,920	72,850	0,048	40,000	0,714	4	4	62,01	4
Machine 8	1	3	72,940	15,490	76,950	0,065	40,000	0,685	6	8	52,44	8
Machine 9	1	3	92,633	98,570	94,020	0,010	40,000	0,540	7	1	90,35	6
Machine 10	1	3	83,358	41,590	86,710	0,024	39,800	0,600	8	9	78,63	1

Figure 74. New matrix of evaluation with the insertion of new indicators

After the calculation of the thresholds and the import of the weights a new ranking of the machines is obtained, according to Figure 75.

↓ Classification	Machine #1	Machine #2	Machine #3	Machine #4	Machine #5	Machine #6	Machine #7	Machine #8	Machine #9	Machine #10
A				X				X		
B		X			X		X			X
C	X		X			X			X	

Figure 75. New ABC rating with new indicators

7.2.4 Assignment of machines under aspects of criticality

After sorting the items (in this case, machines) the respective ranking is performed. For this, the Promethee technique is used through Visual Promethee software. The evaluation matrix and the parameters are shown in Figure 76.

Criticality Analysis	OEE	MTBF	Availability	Failure Rate	Production C...	Security Cost	Safety Risk	Severity Rating
Unit	%	Time	%	unit	$	$	1-9	1-9
Cluster/Group								
Preferences								
Min/Max	max	max	max	min	min	min	min	min
Weight	0,14	0,13	0,11	0,11	0,13	0,09	0,14	0,14
Preference Fn.	Usual	Usual	Usual	Usual	Usual	Usual	Usual	Usual
Thresholds	absolute	absolute	absolute	absolute	absolute	absolute	absolute	absolute
- Q: Indifference	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
- P: Preference	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
- S: Gaussian	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Statistics								
Minimum	70,04	15,49	72,85	0,01	39,00	0,06	1,00	1,00
Maximum	92,63	98,57	94,02	0,07	40,00	0,71	9,00	9,00
Average	82,57	45,43	85,35	0,03	39,82	0,56	5,00	5,20
Standard Dev.	8,51	29,55	8,06	0,02	0,30	0,18	2,83	2,48
Evaluations								
Machine 1	89,63	40,00	91,88	0,03	40,00	0,06	8,00	8,00
Machine 2	82,74	25,29	86,50	0,04	39,60	0,60	1,00	6,00
Machine 3	90,46	62,80	93,65	0,02	39,80	0,55	9,00	4,00
Machine 4	70,04	20,92	72,85	0,05	40,00	0,71	3,00	2,00
Machine 5	81,24	30,16	84,10	0,03	39,80	0,61	1,00	5,00
Machine 6	92,63	98,57	94,02	0,01	40,00	0,54	3,00	5,00
Machine 7	70,04	20,92	72,85	0,05	40,00	0,71	4,00	4,00
Machine 8	72,94	15,49	76,95	0,07	40,00	0,69	6,00	8,00
Machine 9	92,63	98,57	94,02	0,01	40,00	0,54	7,00	1,00
Machine 10	83,35	41,59	86,71	0,02	39,00	0,60	8,00	9,00

Figure 76. Criticality Matrix - Promethee

The units of the quantitative and qualitative indicators and the criteria allocated in a single cluster were parameterized. In the “Preferences” tab was defined whether the criterion has to be minimized or maximized. The weights were imported from the evaluation of the indicators (Figure 60). The preference function “Usual” was selected, to suit the standard values of the indicators. In fact, it corresponds to optimization: the higher the value, the better. Does not include any limits. It is understood as the right choice for the criteria, as in some very different assessments. The thresholds were selected as "absolute" as they were expressed in the measurement scale criterion.

The values of the indicators for each machine were imported manually from Excel, the quantitative data extracted from the statistics of the logs and the qualitative ones converted to a specific scale with randomly generated data also from Excel. Statistical calculations are performed automatically by Visual Promethee, elucidating data of the maximum and minimum values of each indicator, the means and standard deviations. The decision matrix is then analyzed for the prioritization of the machines in relation to the adopted criteria.

Among the analyzes performed by the software used is the "Promethee Diamond", which consists of presenting the ranking of the Promethee through a representation in two dimensions, plotting the positive (Phi+) and negative (Phi-) preference flows in a screen with angle of 45°. The results of the evaluation are presented in Figure 77.

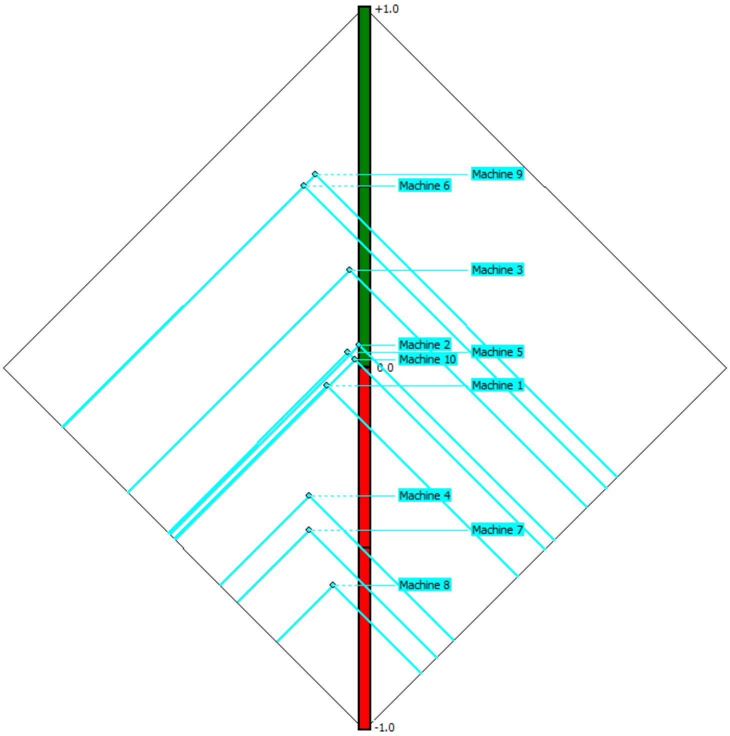

Figure 77. Assignment of machines using the Promethee method

A 45° cone is formed for each machine. The tip of the cone corresponds to the values of the flows of preference of each machine. When one cone is on top of another, this machine is preferred over the other in the ranking. Due to the mathematical properties of the preference flows, the cones are located on the left side of the vertical axis.

Thus it is possible to observe Machine 8 being the most critical of the evaluation and Machine 9 the least critical. As the objective of this stage is the ranking of the machines with respect to the levels of criticality, we present the results in Figure 78, from the least critical machine to the most critical one.

Rank	Action	Phi	Phi+	Phi-
1	Machine 8	-0,5993	0,1561	0,7554
2	Machine 7	-0,4466	0,2	0,6466
3	Machine 4	-0,3519	0,2472	0,5991
4	Machine 1	-0,047	0,4243	0,4713
5	Machine 10	0,0247	0,4984	0,4738
6	Machine 5	0,0434	0,4987	0,4552
7	Machine 2	0,0639	0,524	0,4601
8	Machine 3	0,2714	0,6147	0,3432
9	Machine 6	0,5058	0,6682	0,1624
10	Machine 9	0,5356	0,6989	0,1633

Figure 78. General ranking from Visual Promethee

In the same way as the analysis based on the ABC classification, in the ranking were inserted the two new indicators for a new evaluation (Reliability and Economic Cost Risk). The new evaluation matrix is presented in Figure 79.

Criticality Analysis	OEE	MTBF	Availability	Failure Rate	Production C...	Security Cost	Safety Risk	Severity Rating	Reliability	Economic Co...
Unit	%	Time	%	unit	$	$	1-9	1-9	%	1-9
Cluster/Group										
Preferences										
Min/Max	max	max	max	min	min	min	min	min	max	min
Weight	0,12	0,11	0,10	0,09	0,11	0,07	0,12	0,12	0,07	0,07
Preference Fn.	Usual	Usual	Usual	Usual	Usual	Usual	Usual	Usual	Usual	Usual
Thresholds	absolute	absolute	absolute	absolute	absolute	absolute	absolute	absolute	absolute	absolute
- Q: Indifference	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
- P: Preference	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
- S: Gaussian	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Statistics										
Minimum	70,04	15,49	72,85	0,01	39,00	0,06	1,00	1,00	52,44	1,00
Maximum	92,63	98,57	94,02	0,07	40,00	0,71	9,00	9,00	90,35	8,00
Average	82,57	45,43	85,35	0,03	39,82	0,56	5,00	5,20	73,81	5,30
Standard Dev.	8,51	29,55	8,06	0,02	0,30	0,18	2,83	2,48	12,25	1,90
Evaluations										
Machine 1	89,63	40,00	91,88	0,03	40,00	0,06	8,00	8,00	77,88	7,00
Machine 2	82,74	25,29	86,50	0,04	39,60	0,60	1,00	6,00	67,34	5,00
Machine 3	90,46	62,80	93,65	0,02	39,80	0,55	9,00	4,00	85,28	4,00
Machine 4	70,04	20,92	72,85	0,05	40,00	0,71	3,00	2,00	62,01	7,00
Machine 5	81,24	30,16	84,10	0,03	39,80	0,61	1,00	5,00	71,78	5,00
Machine 6	92,63	98,57	94,02	0,01	40,00	0,54	3,00	5,00	90,35	6,00
Machine 7	70,04	20,92	72,85	0,05	40,00	0,71	4,00	4,00	62,01	4,00
Machine 8	72,94	15,49	76,95	0,07	40,00	0,69	6,00	8,00	52,44	8,00
Machine 9	92,63	98,57	94,02	0,01	40,00	0,54	7,00	1,00	90,35	6,00
Machine 10	83,35	41,59	86,71	0,02	39,00	0,60	8,00	9,00	78,63	1,00

Figure 79. Promethee matrix with two new indicators

Using the same parameters from the previous analysis and adding two new indicators, we have the representation of the Diamond Promethee (Figure 80). Figure 81 presents the new ranking extracted from Visual Promethee software.

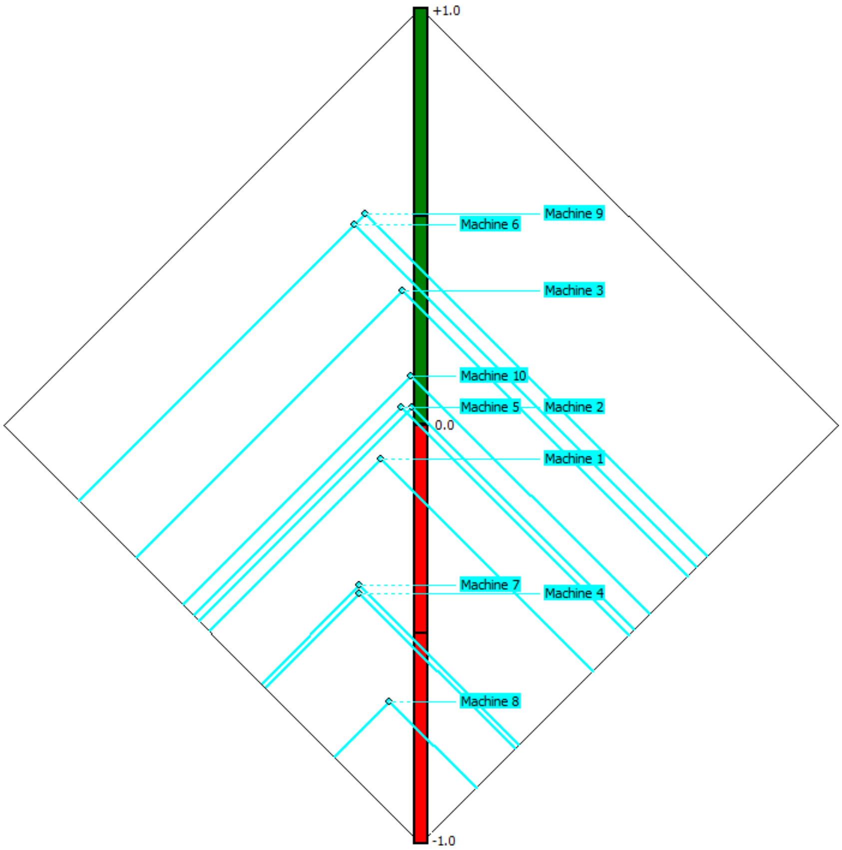

Figure 80. Promethee ranking perspective with two new indicators

Rank	action	Phi	Phi+	Phi-
1	Machine 8	-0,6592	0,1329	0,7921
2	Machine 4	-0,4	0,2264	0,6264
3	Machine 7	-0,3817	0,2357	0,6173
4	Machine 1	-0,0798	0,4118	0,4916
5	Machine 5	0,0438	0,4982	0,4544
6	Machine 2	0,0448	0,5116	0,4668
7	Machine 10	0,1201	0,5482	0,4281
8	Machine 3	0,323	0,6394	0,3164
9	Machine 6	0,4816	0,6606	0,179
10	Machine 9	0,5074	0,6869	0,1794

Figure 81. New general ranking from Visual Promethee

In this new scenario, Machine 8 is presented as the most critical and Machine 9 as the least critical. The information collected in criticality analyzes, under aspects of classification and ranking, will support the analysis of the implementation of appropriated maintenance strategies, according with the next section.

6.2.4 Maintenance Strategies Selection – CEV-ELECTRE approach

With the prioritization of the most critical items of the system, an approach is proposed to select the appropriate maintenance strategies. It is understood that predictive maintenance techniques are honorable and require more specialized technical and human resources, generating a higher cost. A corrective maintenance policy, however, requires fewer resources, making it cheaper for cases where assets are not critical to the process.

Thus, a model for decision-making with regard to maintenance strategies is presented in topic 6.4.3. The Electre Tri method is proposed for this application, to classify the machines in certain maintenance strategies: Reactive Maintenance, Time-based Maintenance, Condition-based Maintenance or Prescriptive Maintenance. The alternatives are the machines and the criteria are raised by the analysis team through the named approach of CEV (Criticality, Efficiency and Viability).

For the present simulation it is defined that criticity is extracted from the ranking of the critical items performed from the previous stage. Efficiency is represented by the calculation of OEE and Viability brings two indicators related to maintenance: (i) maintainability and (ii) maintenance costs. The RCM program team can define other indicators, and insert in the presented decision model. Figure 82 shows the decision matrix of the Electre.

Action	Elow	Ehigh	Criticality	OEE	Maintainability	Maintenance Cost
Machine 1	1	3	0,4916	89,635	0,884	5
Machine 2	1	3	0,4668	82,739	0,658	8
Machine 3	1	3	0,3164	90,464	1,420	1
Machine 4	1	3	0,6264	70,044	0,975	3
Machine 5	1	3	0,4544	81,247	1,140	5
Machine 6	1	3	0,179	92,633	3,133	2
Machine 7	1	3	0,6173	70,044	0,975	7
Machine 8	1	3	0,7921	72,940	0,464	6
Machine 9	1	3	0,1794	92,633	3,133	6
Machine 10	1	3	0,4281	83,358	1,594	5

Figure 82. Decision matrix for selection of maintenance strategies – Electre Tri

The thresholds were then defined, with reference to the value of 1/4 of the range positive and negative. Since the criticality analysis is the main point of the RCM analysis, the weight of 50% is attributed, the other 50% being divided among the other criteria. Figure 83 shows the assigned thresholds and weights (k1 to k4).

	Criticality	OEE	Maintainability	Maintenance Cost
g(b1)	0,639	75,691	1,131	6,25
g(b2)	0,485	81,338	1,798	4,5
g(b3)	0,332	86,985	2,466	2,75
MAX/min	-1	1	1	-1

	Lambda	k1	k2	k3	k4
LB-Lower	0,5	0	0	0	0
UB-Upper	1	1	0,333	0,333	0,333

Figure 83. Thresholds and weights defined for the Electre method

After the analysis is completed, we have the robust assignments of the alternatives in their classes. One machine is prone to the prescriptive maintenance application, three to condition-based maintenance, three to time-based maintenance and three to reactive maintenance. Figure 84 shows the results.

Maintanance Strategy ↓	Machine #1	Machine #2	Machine #3	Machine #4	Machine #5	Machine #6	Machine #7	Machine #8	Machine #9	Machine #10
Prescriptive								X		
Condition-based	X			X			X			
Time-based		X			X					X
Reactive			X			X			X	

Figure 84. Final results of selection of maintenance strategies

Following the dynamics of the criticality classification of the machines, in this stage of selection of maintenance strategies was also performed a new simulation with the extracted data with the insertion of two new indicators. Thus, Figure 85 presents the results, with a reclassification of the machines for the selection of maintenance policies.

Maintanance Strategy ↓	Machine #1	Machine #2	Machine #3	Machine #4	Machine #5	Machine #6	Machine #7	Machine #8	Machine #9	Machine #10
Prescriptive							X	X		
Condition-based	X	X		X						X
Time-based			X		X					
Reactive						X			X	

Figure 85. Reclassification of maintenance strategies selected

The results of the application performed in the simulated process presented are discussed in the following topic.

6.3 RESULTS AND DISCUSSIONS

The application of Smart-RCM in a simulated environment results in interesting data to discuss the importance of using the available data in the company for the application of methodologies with analytics tools to improve the quality of decision making and increase the reliability of industrial processes.

The model of reconciling qualitative and quantitative information demonstrates effectiveness when well developed. When handled correctly, this information becomes a powerful tool in methodologies such as the proposed Smart-RCM.

Smart terminology refers to the ability to process information and make the right decisions. This new methodology based on system selection, risk analysis and selection of strategies for maintenance is a process that companies can use to maintain and optimize all their assets (dynamic and static).

The selection of the system is an "off-line" step, since it is carried out at a strategic level and it is possible to choose which systems are the priority to be adopted from the RCM methodology. This step should be revisited according to changes in company strategies. This issue should be well formulated in the Smart-RCM audit process.

The classification and ranking of the most critical items (in this case, the machines) is a step executed "online", since in its decisions quantitative indicators are used updated in real time (according to the specifications of the information system used). The qualitative indicators can be verified in a pre-defined time by the audit team.

This dynamism of the system, here called "Smart", allows the visualization of changes in the behavior of system assets, a concept directly linked to the advances of Industry 4.0.

In the simulation presented we have the classification and ranking of the criticality of the machines presented with seven indicators. After the presentation of the results, it is suggested to insert two more indicators, totaling nine. The intention was to verify the importance of analyzing what and how many indicators to use, and to observe the behavior of decision models.

Thus, Figure 86 shows the results of the ABC classification using the Electre method, and Figure 87 shows the changes in the machine rankings. Evaluation 1 was carried out with seven indicators and evaluation 2 with nine indicators.

	Machine →	#1		#2		#3		#4		#5		#6		#7		#8		#9		#10	
	Evaluation →	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Class →	A								X							X	X				
	B				X					X	X			X	X					X	X
	C	X	X	X		X	X	X				X	X					X	X		

Figure 86. ABC classification with changes in number of criteria - Electre method

Promethee			
8 indicators		10 indicators	
1	Machine 8	1	Machine 8
2	Machine 7	2	Machine 4
3	Machine 4	3	Machine 7
4	Machine 1	4	Machine 1
5	Machine 10	5	Machine 5
6	Machine 5	6	Machine 2
7	Machine 2	7	Machine 10
8	Machine 3	8	Machine 3
9	Machine 6	9	Machine 6
10	Machine 9	10	Machine 9

Figure 87. Machine ranking with changes in the number of criteria - Promethee

As the indicator with the highest weight (50%) in choosing maintenance strategies comes from the classification presented in Figure 83, online monitoring extends to this decision stage. For example, with changes in this ranking, a non-critical treated machine (C) may be viewed as more critical (B or A) due to the growing importance of this machine in the new monitored indicators.

Also, to choose the maintenance strategies adopted for each machine, the insertion of new indicators directly impacts the decisions. Figure 88 shows the policies selected for the evaluation with 8 indicators (Evaluation 1) and 10 indicators (Evaluation 2).

	Machine →	#1		#2		#3		#4		#5		#6		#7		#8		#9		#10	
	Evaluation →	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Maintenance Strategy →	**Prescriptive**														X	X	X				
	Condition-based	X	X	X				X	X					X							X
	Time-based				X		X			X	X									X	
	Run-to-Failure					X						X	X					X	X		

Figure 88. Results of Selection of Maintenance Strategies

The reclassification is an important approach to the use of the correct maintenance policy for a given machine, being dynamized by the indicators used in the analysis. It is noteworthy that the availability and quality of information (indicators) depends on the level of maturity of the company.

7 CONCLUSIONS AND FUTURE WORK

The maintenance function continues to evolve and is currently in its fourth generation. In this scenario, several initiatives are presented, focusing on technological advances through industrial Internet of Things (IIoT), predictive analysis, interconnectivity, defect elimination, etc. Smart RCM brings the mainstream of maintenance together with the organization's physical asset management and risk management strategies, addressing 4th generation requirements.

The application of Smart RCM changes the way organizations think about their operations and maintenance. Not only does it challenge the traditional approach to equipment maintenance, moving the company from a perception of breakdown and repair, it also creates a new risk-based asset management culture.

Smart RCM is based on the very robust classic RCM methodology with a new approach to managing the risks associated with preserving asset functions. Risk-based decision logic optimizes the maintenance program (selects the appropriate maintenance policy) while managing physical and economic risks based on its qualitative and quantitative indicators. In addition, it develops methods for the reduction of human error, an important factor for decision making processes.

The adaptation and customization of tools or methodologies applied in the maintenance function has proven to be an important initiative. Structures with contemporary approaches to more flexible and robust models have gained ground in related research. The presented framework brings important insights in the development of the RCM, with a customized and dynamic model, allowing applications of tools widely disseminated by researchers around the world.

The extraction of indicators from current literature brings an innovative approach within the scope of RCM, presenting a well-structured and systemic method that can be revisited and updated to suit new research in RCM applications.

The research reinforces an important relationship between tacit and explicit data, proposing an integration and generation of a single knowledge base for later use in the stages of the RCM development. The structuring of qualitative and quantitative data using appropriate tools constitutes a consistent database. The DMD approach serves as an example of data fusion and can be used in methodologies other than RCM.

A customized model for RCM deployment is presented, focusing on decision making processes. Compared to traditional models, it is simplified by reducing the deployment stages, improving the knowledge and possible techniques applicable to data processing (mining) in quantitative data and applying MCDMs in decision processes.

Using classic RCM publications coupled with contemporary standards and publications makes Smart RCM a modern approach focused on managing company assets. Management tools support strategic decision levels, generating a systemic and global view of the system.

The level of maintenance maturity should be observed and mapped in the planning phase of the RCM, since it may compromise the use of the proposed framework, given the information poverty and the lack of structure for deployment success. Models of multicriteria decision-making and analytics depend on these requirements to be applied. Thus, the availability and access to process and maintenance information are important for Smart RCM, and a careful evaluation of these databases is necessary for a better exploration of the methodology. It is worth mentioning that the proposed model is passive of adaptations to the context of the company.

Concepts of MA (Maintenance Analytics) are highlighted as it brings innovations in data collection and processing, decision analysis with multicriteria decision making tools, typical approaches of Industry 4.0 context.

With the application of Smart-RCM in a simulated environment, it was possible to observe the dynamics model through the obtained results. The classification and reclassification of the criticality presents these dynamics through the changes made in the simulations.

The Smart-RCM proposal is passive of future efforts in the application of Artificial Intelligence subfields, bringing the possibility of genuine interaction between humans and machines. Machine learning concepts can support the automation of the analytical models used, through neural networks, statistics, operational and physical research to find information hidden in the data. In addition, the model can be subjected to other future improvements, such as:

(i) an analysis of the decision model sensitivities can be conducted to enable a better understanding of the value dynamics of alternatives to changes in parts of Smart-RCM. This analysis is important as it contributes to the decision maker's understanding of the scope and limitations of the problem;

(ii) mapping and application of scientific methods to analyze decision-making processes, from the perspective of quality criteria, information and decision.

(iii) conceptual development and implementation of a dynamic "module" to define the periodicity of maintenance actions;

(iv) Smart RCM implementation in a real scenario, to check the deployment steps, watching activities related to the professionals involved, to explore possible process adjustments. The practical experiment was carried out at the machine level, depending on the characteristics of the model (simulated environment) used. With a real application it would be possible to lower the level of this analysis for equipment or components, which would bring a better assessment regarding the maintainability of these elements.

(v) design and development of an RCM module in maintenance management software. With an intuitive and easy-to-use environment, it should integrate all the tools used for best use in Smart RCM deployment.

Smart-RCM emerges as a new approach in the Maintenance 4.0 scenario, bringing important concepts of system criticality, fault analysis and their effects, exploring operational, environmental and safety aspects. This makes it possible to optimize the criticality assessment processes of industrial systems, significantly supporting the choice of the best maintenance strategies, resulting in better results in meeting business goals, increasing plant reliability and reducing costs.

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