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# A Capability Assessment Model of Industry 4.0 Technologies for Viability Analysis of PoC (Proof Of Concept) in an Automotive Company

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**Abstract.** Due the increase of demand for the optimization of productive processes and the use of information at industries. Based on this, it has been highlighted some initiatives that are being adopted by manufacturing, such as Predictive Maintenance, focused on increasing the useful life of equipment to get a more flexible production. The predictive maintenance has the purpose of, with the support of relevant data collected through smart sensors, constructing a diagnostic which allows any maintenance staff to comprehend a machine's health and plan possible interventions in the production line. However, it has been noticed that there are numerous challenges in implementing this concept in corporations due to unmeasured technical, organizational and cultural factors. The objective of this article is to evaluate the capability of the Industry 4.0 technologies in relation to the functional requirements according to the PoC (Proof of Concept) of Predictive Maintenance within the automotive industry for the construction of a Referential Architecture. It was developed through the association of attributes, functional requirements and applicable technologies supported by multi-criteria analytical decision-making methods (MCADMM). The RAMI 4.0 framework was used to structure the layers of strategic implementation of the initiatives belonging to Industry 4.0 (I4.0). Specialists were consulted, through a Survey, to collaborate on the evaluation of the relational framework between functional requirements and applicable technologies. The results presented which are the most significant technologies at each strategic level of RAMI 4.0, thus characterizing a Referential Model for Predictive Maintenance initiative in the automotive sector.

**Keywords.** Predictive maintenance, industry 4.0, PoC, RAMI 4.0, Referential architecture.

## Introduction

Due to the increasing demand for integrated systems, communicating and sharing information among themselves, there is a need for study in relation to this process, since this does not only involve technological requirements, it also includes the organizational process and the strategic part of the company. The goal is to use this information efficiently to improve the production process, making it more agile.

The context of this change in the industrial environment emerged at the Hannover fair in Germany in 2011. It brought new concepts, business models and values that had not been seen and addressed previously, connecting data from inside and outside the industry through communications networking and services based on CPS (Cyber Physical Systems), IoT (Internet of Things) and IoS (Internet of Service) [1].

The presentation of technologies and concepts from Industry 4.0 may appear to be very broad and complex at first glance. Systems become adaptive and learn to control, autonomously, production. Employees will be faced with changes in their operating routines, enabling them to assume a broader range of responsibilities. They should assist the machine, where the system will notify the measures that must be taken. After the user's decision making, the system will learn how to proceed in each situation [2].

A specific application situation would be the use of advanced systems in conjunction with Cloud and CPS technologies in order to avoid possible machine performance problems in the production line. A self-conscious system can self-assess its integrity and condition, and use similar information to perform an analysis and apply it in predictive maintenance, avoiding potential problems, and optimizing equipment integrity [3].

In the face of changes in the industry scenario, each company must strategically carry out an assessment of the technological level and the functional requirements for concepts implementation, such as the predictive maintenance of Industry 4.0 [2]. In this way, it will be possible to analyze and understand which technologies would be most significant for each company. Thus, allowing a broader view of how to apply the proofs of Digital Transformation concepts within the organization.

The challenge of this research is to obtain the functional requirements and technologies related to Digital Transformation, which will constitute a reference model for the implementation of a Proof of Concept for Predictive Maintenance. It is possible to scale the Functional Requirements (FRs) with the technical resources, thus developing a referential architecture so that the organization can evaluate its ability to insert criteria specific to the concept that one wishes to introduce.

This paper aims to identify the functional requirements and applicable technologies of Industry 4.0, focused on predictive maintenance, in order to obtain a referential architecture, allowing to evaluate which technologies meet the concept to be implemented.

## 1. Literature review and related works

### *1.1. Industry 4.0*

According to the literature [1] the concept was first presented at the Hannover fair in 2011, such as Smart Factory or Smart Manufacturing, however, it became popularly known as Industry 4.0, or Fourth Industrial Revolution. Each of the revolutions was marked by specific characteristics and modified the industry of its time.

- **First Industrial Revolution**: It began in England at the end of the 18th century in fabric factories. It was marked by the use of steam powered machines.

- **Second Industrial Revolution**: It occurred in the early twentieth century and was marked by the use of electricity and mass production, based on division of labor.
- **Third Industrial Revolution**: It happened in the early 1970s and is present to this day. Its main feature is the great development of electronics and the use of electronic components. The use of computing and automation also leverage the entire production process.

Industry 4.0 considered the fourth revolution, is in turn characterized also by the concepts of CPS, IoT and Cloud Computing. The connection between the real world and digital has become very present, which is mainly due to the use of smartphones, which created a network of access between people and information systems, this being one of the factors that brings the theme Internet of Things and Internet of Services. This increase in connectivity not only affects people's lives, but also leads to permanent changes for the industry. The increasing automation of production processes, the development of intelligent systems for monitoring and decision making, are strong trends in industries.

Industry 4.0 is known as a range of technologies, which must operate together, in order to result in increased efficiencies throughout the production system and to obtain more information about the process [4]. In addition to avoiding losses, consequently the process becomes more reliable generating a performance increase. Communication between machines and equipment requires communication protocols, and this is due to the fact that it is no longer simply about transmitting data. These protocols shall be capable of describing the data in such a way as to be accessible and interpreted for such equipment. This will allow other systems and machines to take action, based on this information. Based on a systematic review in the literature [5], there are examples of technologies and concepts from this revolution that can be applied in the case of predictive maintenance. For example: cloud storage, wireless industrial networks and integration technologies (Gateways).

### *1.2. Reference Architectural Model Industrie 4.0 (RAMI 4.0)*

It is possible to find in the reading several models of architectures references and frameworks on the I4.0, the great majority developed by companies' experts in the area of consultancy and technology. The RAMI 4.0 (Reference Architectural Model Industrie 4.0) framework, developed by the German company PLATTAFORM INDUSTRIE 4.0 in 2016 [6] has a more technological proposal in relation to the other frameworks until then, approaching the purpose of the present project. Therefore, the basic architecture model adopted for the theoretical reference of this work will be RAMI 4.0. The justification of choice for the use of this reference architecture as support is due to the fact that it is possible to apply each of the layers of the model on a perspective of predictive maintenance.

In predictive maintenance this hierarchy becomes necessary since it involves and impacts several levels within a company. From the plant floor level to the strategic level, we will work with the information and make decisions on top of these data. In order to use the RAMI 4.0 framework [7] as a reference support architecture in the research, it is necessary to relate the predictive maintenance with the framework in question. Considering the architecture of the RAMI 4.0 framework, some considerations must be made about what each of the elements in the framework architecture represents when it comes to predictive maintenance.

Thus, each layer of RAMI 4.0 was seen under what its functionality would be and what it would correspond to when it was treated for predictive maintenance. The considerations made in this work were as follows:

- **Assets**: Of extreme relevance in predictive maintenance, the elements that make up this level were considered the sensors, since they are the real physical elements, which interact directly in the process.
- **Integration**: The elements belonging to this level have great importance within the case in question, are the gateways, that is, bridges elements, that present the function of relating domains, interconnecting networks, transmitting and transforming the data coming from the sensors for a same type of protocol.
- **Communication**: As in the model of referential architecture itself, as in the case of predictive maintenance, this level aims to make the information accessible to other instances belonging to the process. In maintenance, tools such as Cloud and Mobile technologies perform these functions.
- **Information**: From the perspective of this work, this level has the function of storing, treating and making useful all the information for the maintenance process. Technologies such as Big Data Analytics and Cloud play an important role in this case.
- **Functional**: At this level, the considerations made were about the functional requirements of predictive maintenance, considering what attributes are required to satisfy it efficiently and the requirements that address it in such a way.
- **Business**: As in the perspective presented by RAMI 4.0 [6], in the maintenance chain, this level also refers to the organizational and strategic part of the company. When applying the referential model in this case, it was necessary to evaluate what would be the elements and factors of the company, at the strategic level, that would be committed to the maintenance, and what would be the attributes and requirements demanded.

### *1.3. Predictive Maintenance*

Changes in the industrial environment are enabling the maintenance industry to have access to advanced technologies and innovation initiatives, such as predictive maintenance. The companies that adopt this methodology are focused on becoming more competitive and efficient. They need to adopt emerging technologies, based on cyber-physical systems to improve their productivity and mitigate problems during the production process [8]. Predictive maintenance is the periodic monitoring of equipment or machines, through data collected through monitoring or continuous inspections. This type of maintenance has the ability to predict the useful life of components, machines, equipment and the best operating conditions. Through this concept, it is possible to anticipate the need for maintenance services, eliminating unnecessary sudden stops of the machines, generating, thus, gain of performance to the productive process.

One of the attributions given to predictive maintenance is the ability to quickly and efficiently determine the causes of failures and propose maintenance decisions, while minimizing the need for human intervention for this [9]. Of extreme importance is the way information can be used to detect, predict, and decide, within a time that brings about efficient results.

The evaluation of the health status of the equipment is done in an uninterrupted manner, and one of the challenges presented in this respect is the difficulty of identifying the relevant parameters in the equipment [10]. Identifying these parameters is extremely important because they will be the indicators on which the diagnostic results will be based. One of the proposed solutions [11] to minimize or even solve this problem, is always to try to increase the range of analyzed parameters, and try to obtain relations between them. In one of the case studies presented in the article, in an industrial compressor a relationship of the oil analysis with the vibration analysis was obtained, somehow these parameters were related in this case, and when analyzed together, they presented more efficient and predictive results compared to the individual analysis.

The acquisition of the equipment information, carried out by the sensors, which in turn transmit and transform this information, so that optimization algorithms can be applied, along with analysis techniques, model comparison and fault histories [12]. After the analysis, a diagnosis is generated, which will include the health status of the equipment and information that will aid in the decision making, with the indication of future failures, based on historical and statistical [13]. The predictive maintenance qualification is given by the efficiency of the computational analysis (Analytics), and can predict the loss of performance of the traditional model machinery (corrective and preventive) based only on the history of failures and corrective actions [14].

## 2. Development of referential architecture

This paper has as reference a framework whose purpose is to facilitate and streamline the process of implementing PoCs (Proofs of Concept) in the scenario of the Brazilian automobile industry. The framework in question is RDPM 4.0 and its objectives are: the development of a referential architecture; a maturity assessment and a functional architecture, all of which are geared towards serving the industry 4.0. However, it is important to emphasize that predictive maintenance is one of the topics that are the implementation of the technologies of industry 4.0 and will be the case study for this paper.

The objective in this work is to focus on the referential architecture phase, whose importance is to provide previous information in relation to the concept (in the scope of industry 4.0) which one wishes to implement in the company. The decision to use a reference model as support (RAMI 4.0 in this case) was extremely significant in the result of this review, because the model used was divided in layers, the research was oriented individually for each one, making it more objective and precise. The technologies found in the literature, in addition to being committed to meeting the functional requirements, should be related to the scope of the RAMI 4.0 layer in which these functional requirements meet and obviously within the scope of applicable technological innovation.

In order to evaluate the technologies identified for each case, it is necessary for the evaluator to have knowledge about the instantiation in which the maintenance will be applied, in order to identify which technologies, apply to the case being evaluated. As for the objective of the attributes, they are responsible for qualifying the predictive maintenance within each layer. The functional requirements in turn must support the attributes so that they are supported [15].

As it is shown in Figure 1, with the aid of RAMI 4.0, it is possible to relate the functional attributes and requirements found in the literature review for each of the layers of the framework, for this relation will be made use of MCADMM AHP (Analytic Hierarchy Process). To define the degree of importance of each attribute and each functional requirement, experts in the area of predictive maintenance were consulted through a survey (relating attributes and functional requirements). With the results of the survey the AHP method is implemented and will bring results that will be used as input to the MCADMM PROMETHEE (Preference Ranking Organization Method for Evaluation) implementation. This method is related to the functional requirements and the applicable industry technologies 4.0 found in the literature, whose implementation will rely on the results of the AHP method, the results of a survey (relating functional requirements and applicable technologies). The results of PROMETHEE will be the referential architecture in question, which relates how each applicable technology meets the functional requirements identified.

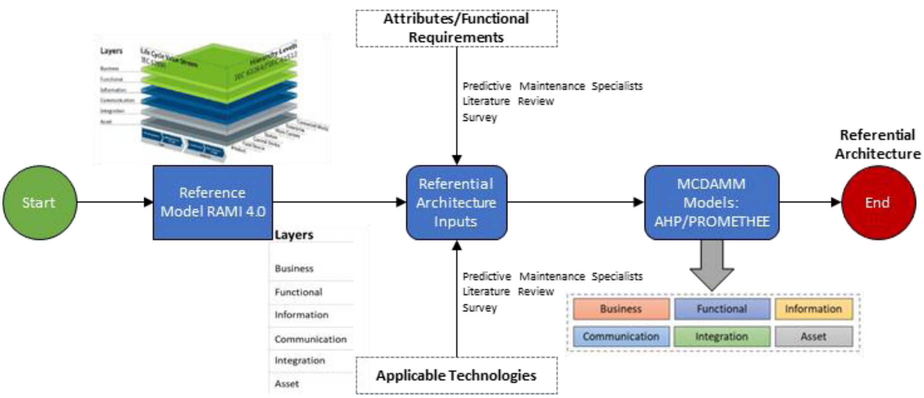


**Figure 1.** Process flow for the construction of the referential architecture.

## *2.1. AHP Model*

The application of the AHP method aims to establish the relationship between the attributes and the functional requirements obtained in the literature of each RAMI 4.0 layer (Asset, Integration, Communication, Information, Functional and Business). This relation is given through the weight that each element has, being this weight directly related to the degree of importance of one element in relation to the other. In this work the degree of importance is obtained through a survey conducted with specialists in the maintenance area.

Figure 2 shows how the AHP models are structured, and 6 models will be structured, one for each layer of the RAMI 4.0 framework. Usually the AHP method is modeled through the Goal layer, Criterion and Alternatives, in this case, it is important to note that there will not be the Alternatives layer, since these will be evaluated in PROMETHEE.

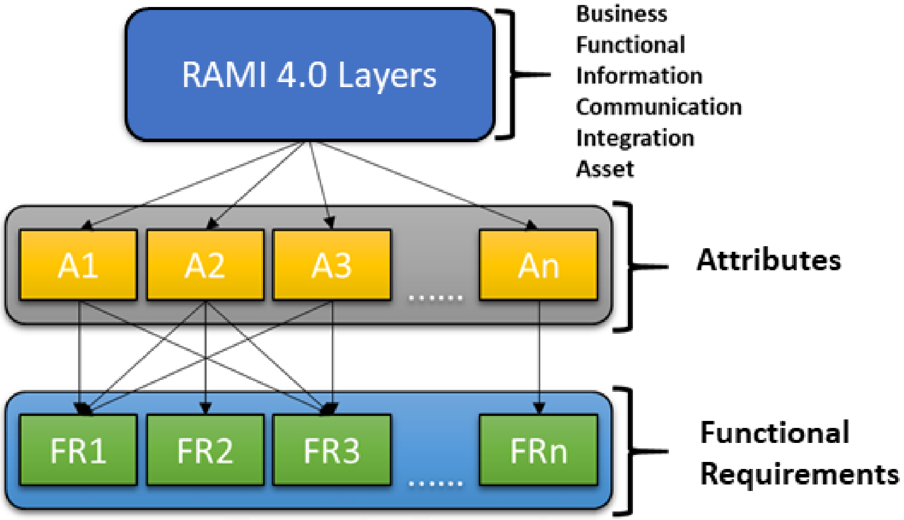


**Figure 2.** Structure of the AHP model.

The results of the AHP method are presented in the form of numerical values that indicate in this case the weight of each attribute and functional requirement evaluated. The results are presented from the perspective of the experts consulted, and it is possible to compare different perspectives within the same scope of evaluation. In this work, two different specialists were consulted, working in different industrial environments, bringing different views to the evaluation.

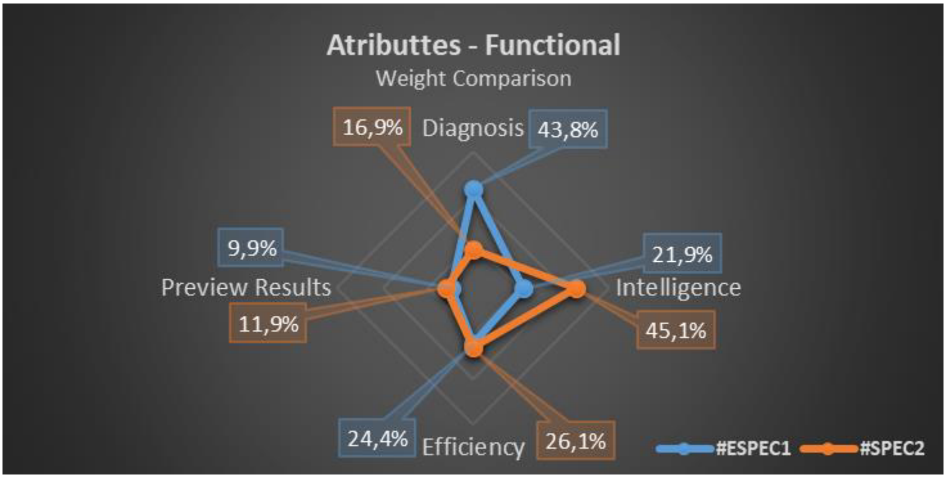


**Figure 3.** Attribute results graph for functional.

The attributes obtained in the literature and evaluated (for the functional layer) are shown in Figure 3, which presents a graph of results of the AHP model, from the perspective of two different specialists (#ESPEC 1 and #ESPEC 2). The attributes evaluated for this layer address aspects directly related to the objective of predictive maintenance, i.e., which attributes it must meet to bring better results from each specialist. The divergence in results is given by each of the specialists acting in different industrial environments and have different perspectives on each attribute or functional requirement.

The functional requirements obtained for the functional layer are presented in Figure 4, which shows a graph comparing the weight of each of the functional requirements belonging to the functional layer, from the perspective of each of the experts consulted in the survey (#ESPEC 1 and # SPEC 2). As well as the attributes of this layer in question, the functional requirements are directed to support the preferences and needs of each company.

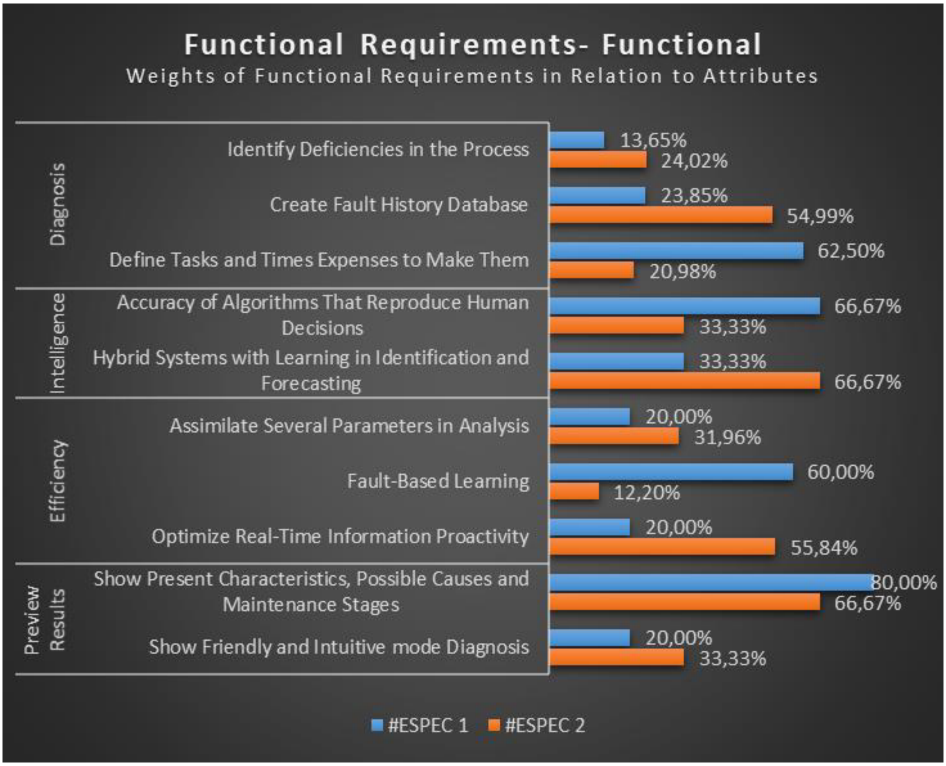


**Figure 4.** Graph of results of functional requirements for functional layer.

## *2.2. PROMETHEE Model*

The application of the MCDAMM PROMETHEE is the final objective of this work, the reference architecture that is characterized in the relationship between the functional requirements and the technological solutions applicable to predictive maintenance. This reference architecture ranks the technologies found in the literature in order to best meet the functional requirements within each sphere (RAMI 4.0 layers) of the predictive maintenance and its results are obtained by importing the results obtained by the AHP method.

In Figure 5 the applicable technologies (referring to the functional layer) and the result of the application of the PROMETHEE model in this layer are presented, from the perspective of the evaluation of one of the specialists consulted (#ESPEC 1 in this case). The result is displayed so that the greater the value Phi associated with the alternative, greater its impact in to attend the functional requirements evaluated.

PROMETHEE Flow Table

| Rank | action | Phi | Phi+ | Phi- |
|---|---|---|---|---|
| 1 | Big Data Analytics | 0,8191 | 0,8257 | 0,0067 |
| 2 | Deep Learning | 0,4023 | 0,5436 | 0,1413 |
| 3 | Inteligencia Artificial | 0,3954 | 0,5439 | 0,1485 |
| 4 | Sistemas Hìbridos | 0,3815 | 0,5420 | 0,1604 |
| 5 | Machine Learning | 0,3292 | 0,4888 | 0,1596 |
| 6 | Fuzzy-Logic | -0,1405 | 0,2932 | 0,4336 |
| 7 | OODA Loop | -0,2211 | 0,2591 | 0,4802 |
| 8 | Mobile | -0,5098 | 0,1036 | 0,6135 |
| 9 | IoT | -0,6040 | 0,0482 | 0,6523 |
| 10 | Virtual Reality | -0,8520 | 0,0000 | 0,8520 |

**Figure 5**. Results of alternatives in PROMETHEE for functional layer - Specialist 1.

## 3. Conclusion

It was demonstrated that it is possible to obtain a referential architecture that relates the functional requirements and applicable technologies that were found in the literature review of a sphere (RAMI 4.0 framework layer) of the predictive maintenance. The evaluation can be performed from the perspective of one or more experts, allowing the results to be compared, implying a more critical view of the best option and can generate more solutions to suit the same case. This paper provides a method that can be replicated and used in several companies and industries and it is also possible to combine the analysis with a maturity evaluation of the company, to see the level that the company is in relation to what was expected. If done in advance to analyze an investment, can identify the best technologies to attend the needs of each company which can cause enormous savings to the company and indicate if the investment is being made at the best option.

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