Simplified Fuzzy Dynamic Cognitive Maps Applied to the Maintenance Management of Electric Motors

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Abstract— Systems and machines must operate under satisfactory conditions to attest to the quality of its production. Using Fuzzy Cognitive Maps based in concepts of the Reliability Centered Maintenance in order to obtain quantitative feedback to support the decision-making process and maintenance strategy, as proposed in this research, one can propose great reliability. This article presents Reliability Centered Maintenance (RCM) through a generic maintenance checklist for electric motors. Through fault and / or fault correction maintenance procedures, a simplified Cognitive Fuzzy Dynamic Map (sDFCM) that will present a quantitative diagnosis offering a computational tool to assist in maintenance management, providing upgrades to the system or machine can model it.

Keywords— Reliability Centered Maintenance, Management Maintenance, Electric Motors, Fuzzy Cognitive Maps, Quantitative Analysis.

I. INTRODUCTION

The rapid development of the industrial process, from the Industrial Revolution (seventeenth century), provoked within the industry, as a whole, the technological evolution. This fact has changed the importance of maintenance, aiming to provide greater quality and competitiveness for the manufacturing sector. This scenario indicates that more and more companies, to achieve what is called "World-Class Performance", are demanding great efforts to improve quality, productivity, and reduce costs, having a direct impact on effective maintenance [1].

Electric motors are extremely energy efficient. These devices, in a production system due to their importance, must have a maintenance schedule. Although engines have highly efficient parts, like any other equipment, are still susceptible to failure. When the fault happens, the drive can be sent to be rewound or a new engine is purchased to replace the faulty one. Failure of the electric motor may result in loss of capacity as well as excessive repair and maintenance costs.

By routinely performing corrective, preventive and predictive tasks, the life of an engine can be extended, and it is efficiency improved. Some companies describe their maintenance procedures so that each maintenance team follows the same methodology. On the other hand, in most countries of the world, electric motors consume up about 66% of the electricity generated. On average, the energy consumed by an induction motor during its life cycle is 60–100 times the initial cost of the motor [2].

For Tsang, the evolution of maintenance techniques and methods needs to prioritize current operational strategies, expectations of environmental preservation and security by society, technological changes, increasing environmental and organizational changes [3]. Thus, the main objective is to present the methodology MRC - Maintenance Reliability Centered regarding an analysis in electric motors. The specific objectives of this work are to present a brief rationale on Reliability Centered Maintenance, to suggest Fuzzy Cognitive Maps (FCM) to quantify maintenance reliability and provide maintenance reliability level feedback. However, the suggested FCM is still at the level of belief, that is, according to the view of experts or specialists. So, the need for maintenance management of this equipment becomes essential. Conceptually, maintenance is the activity that seeks to preserve the technical characteristics of an equipment at the level of its specified performance.

The maintenance of equipment and machinery must include technical knowledge and administrative procedures to maintain its characteristics of functionality, safety and environmental. Otherwise, the maintenance must allow the equipment to operate ensuring the continuous production of the company and / or industry, besides preventing failures that may partially or fully harm the production line involved.

The application of maintenance strategies focuses directly on the particularities of the aging stage of equipment and installations. According to the concept of maintenance and conservation of machines and equipment, it can be mentioned the Reliability Centered Maintenance (RCM) methodology, which is oriented to failures and defects of machines or systems. In short, RCM, in its classic form, is the application of a structured method to establish the best maintenance strategy for a given system or equipment. Thus, the concepts of failure and structured analysis will be used in the development of this research. Even though the proposed tool is in an initial stage, it can be extended and applied in others devices, such as electrical transformers with different powers and specifications.

The main goal of this work is to develop a methodology for the creation of maintenance indicators in industrial electric motors, which will be used to achieve strategic planning in favor of a continuous improvement in the productive process of goods and services. The specific goal of this work is to present a brief background on maintenance's aspects to suggest the Simplified Dynamic Fuzzy Cognitive Maps (sDFCM) to quantify the maintenance reliability level.

The structure of this paper is as it follows. Section 2 conceptualizes aspects of maintenance and industrial maintenance. Section 3 discusses the main aspects of FCM and sDFCM, and presents the approach towards maintenance management inspired on RCM applied in electric motors. Section 4 presents the simulated results, and Section 5 concludes the paper and suggests future works.

II. MAINTENANCE MANAGEMENT CONCEPTS

The management of maintenance systems is a complex activity, especially when there are several contracting companies acting as executors of planned and emergency activities. In particular, the maintenance of electrical motors, due to the need of uninterrupted work in factory floor [4].

In industrial plants, the stoppage for maintenance, in general, generates concern about the scheduling and production progress. The organization must be structured with the purpose of fulfilling the binding requirements, relating technics in the manufacturing process, the personnel involved with the product and maintenance of the machines used in the manufacturing process and the type of product to be manufactured.

The adaptation of all administrative practices with technical and supervisory actions, which happens through direct or indirect equipment processes, shall be aimed at ensuring the safety and efficiency of the functions and standards required in the manufacture or service supply in which the equipment was designed for.

Managing equipment requires a maintenance routine that must involve several actions that configure the best functioning and allow reliability in the process in which it is inserted, such as electrical motors in discharge conveyor. In this context, the development of a strategy that indicates reliability levels can be used to help in the management of the maintenance, identifying points of possible improvements in the quality, e.g. the technical knowledge of the manpower.

It is not the scope of this work to substantiate the types of maintenance. Only the concepts required for maintenance management inspired by the RCM technique by means of an sDFCM will be aproached.

The types of classic maintenance considered in the development of this work are:

- Corrective Maintenance: performed when a failure occurs over certain equipment. It can be planned when the equipment indicates symptoms that its operation is not under normal conditions, or that the cost-benefit relation to Preventive Maintenance is more interesting and profitable. It is also identified as unplanned, where an unexpected failure occurs and a rapid corrective action is required.
- Preventive Maintenance: indicated when it is necessary to replace parts or recover the equipment. This type of maintenance analyzes the best moment for the maintenance to happen in critical equipment, preventing the manifestation of failures.
- Predictive Maintenance: it requires a constant monitoring of the equipment through more sophisticated instruments, which allows equipment's maintenance before a break happens and it stops working. Some of the main methods used to monitor equipment, vibration analysis, thermography analysis, noise analysis, insulation resistance, rolling check among other potential problems.

The goal of this work is to develop a maintenance strategy inspired by the RCM through the occurrence of faults and defects, and predictive and preventive maintenance levels in industrial electric motors, aiming the construction of a tool to assist on decision-making process regarding failures and defects, especially failures. Thereby, it is important to define:

- Defect: an anomaly in equipment that can cause it to operate irregularly or below its rated capacity. If not corrected in time, it can evolve and cause the equipment to fail and be removed from service.
- Fault: an anomaly in equipment that necessarily requires the interruption of the equipment in operation, i.e. withdrawing it from service.

Failures and defects can be expanded in more complexity levels, but the purpose of this work is to develop a tool for diagnosis by the frequency of their occurrence and not intrinsic analysis of the causes. Thus, reliability can be defined as the ability of an item to perform a specified required function over a given time interval. Failures can be classified by their origin, speed and manifestation [5].

There are several maintenance management strategies in the literature [6], among them it is noteworthy citing the RCM. The RCM is a technique used to develop cost-effective maintenance plans and criteria so the operational capability of equipment is achieved, restored, or maintained. Its main objective is to reduce the maintenance cost by focusing on the most important functions of the system. There are several different formulations of RCM processes in the literature. The RCM analysis may be carried out as a sequence of activities or steps.

The use of a checklist is usual in maintenance management for standardization and recording the sequence of the actions to be performed. The execution frequency of the check list procedures is of paramount importance, since some inspected items require annual, monthly, weekly or even daily monitoring and should be defined by the area experts [7]. The priority regarding the activity developed in maintenance should also be determined. Priorities are stipulated according to the importance and nature of the machine. A priori, suggestions of the main actions are presented, in a summarized way, adopted by the authors or specialists. This work's proposal is to use the

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concepts discussed and associate them to a checklist applied to electric motors, as presented in Table 1.

It is expected that one of the contributions of this research is the modeling of a maintenance management strategy, even though it is necessary to define its frequency of execution using suitable models. Thus, the development of a cognitive model that represents the management inspired by the concepts of Reliability Centered Maintenance prioritizes the representation of the concepts of potential failure / defect and functional failure / defect.

TABLE I. CHECKLIST MAINTENANCE IN ELETRIC MOTORS

Item	Maintenance actions description
01	Engine board data in the environment.
02	Check vibrations and noises outside of standard.
03	Grease bearings.
04	Measure and record voltage and current between phases.
05	Check status of lubricant types.
06	Measure and record the insulation resistance.
07	Measure and record temperature of the bearings and the wound elements.
08	Check and correct the condition of the seals or ring.
09	Vibration monitoring.
10	Visual inspection.
11	Motor circuit analysis.
12	Grounding situation.
13	Machine Reliability Level.

III. DYNAMIC FUZZY COGNITIVE MAPS APPLIED TO MAINTENANCE QUALITY LEVEL

This research suggests the use of a sDFCM, a variation of the classic FCM, to assign maintenance quality levels. The initial version of sDFCM1 is implemented in this paper and its complete version (sDFCM1 and sDFCM2, in a future work) to assist decision making in the maintenance management area.

A Fuzzy Cognitive Map (FCM) is a Fuzzy Influence Graph which is a result from the works of some psychologists. “Cognitive Maps” has been first introduced to describe complex topological memorizing behaviors in the rats [8]. Since the pioneering work of Kosko [9], which extended Axelrod's Cognitive Maps [10] by the inclusion of Fuzzy Logic, several applications of FCM have emerged in the literature in several knowledge areas. Some applications of the FCM and its variations can be found in the literature in the areas of artificial life [11] [12], spot detection in images generated by the stereo camera system [13], mobile robotics [14], decision making in the medical field [15]. Besides, time series prediction [16], multi agent systems [17] [18], process control [19], maintenance management [20], swarm robotics [21], among others. Recently, some studies are using learning algorithms to adjust interaction weights among the factors to overcome drawbacks in FCM [22]. In this way, evolutions of the FCM has appeared, such as ED-FCM (Event Driven-Fuzzy Cognitive Maps) applied in autonomous mobile robotics [23], and DCN (Dynamic Cognitive Networks) on process control [24] [25]. In [18] a formal adaptation of the original FCM is presented, this new tool is designated as TAFCM (Timed Automata Fuzzy Cognitive Maps). These are just a few of several examples that can be found in the literature.

Thus, Gonzalo and collaborators recently suggested that the Fuzzy Cognitive Maps (FCMs) are powerful tools for modeling dynamic systems. FCMs describe expert knowledge of complex systems with high dimensions and a variety of factors. An increased interest about the theory and application of FCMs in complex systems also has been noted. In short, FCMs are powerful tools for modeling dynamic systems. Although FCM are considered as neural systems, there are major differences regarding other types of artificial neural networks (ANN) [26]. In this way, according [17], the fundamental difference between FCM and ANN is that all nodes of the FCM have a strong semantic.

In general, the FCMs can be developed in two different ways, in an automatic way, through historical data, or manually [27]. The FCM used in this research was developed manually, because the causal relationships weights were adjusted empirically, so that the desired output is a quantitative diagnosis through the qualitative opinion of the experts.

Further constructions details of the classical FCM with different mathematical formalisms, inferences types and applications can be found in [28]. Recently, in [29] presents different evolutions of the classic FCM model and its new applications. In this work, especially in chapter 10, an algorithm based on FCM Ontology [30] is presented as development steps of an FCM model, as shown in Table 2.

TABLE II. FCM ONTOLOGY

Steps	Description
1	Identification of elementary concepts, their roles (input, output, decision and level) and their interconnections, determining its causal nature (positive, negative, neutral)
2	Initial set-up of concepts and relationships. The initial state values of the map (nodes/edges) can be acquired from experts, historical data analysis and / or system simulation
3	Determination of ontological influence among concepts. Design of the different ontological views of the system
4	To each view of the system, design of fuzzy rule bases and time varying functions computing the values for the weights of the DFCM fuzzy and/or time-varying relations
5	Design of management level corresponding to the development of the rule base that are associated to and selection relations, and, implementation of algorithm to on-line learning such as reinforcement learning rules
6	Model Validation

The DFCM development has 7 steps; the sDFCM has summarized it down to 6 steps, excluding the step that addresses information processing and dynamic tuning of the causal relationships. Thus, the basic difference between the proposed version and the former one, in this research, is the application of machine learning algorithms for dynamic tuning of the DFCM is not necessary. More information on the development of DFCM can be found in [12], in which it also discusses aspects of DFCM stability, relevant to the development of the cognitive model, as the one used in this research.

Steps 1, 2 and 3 of this algorithm are like classic FCM development. Step 4 is related to the inclusion of fuzzy relations that model cause-effect relationships in the graph. The use of a fuzzy relation allows modeling a relationship with more than a concept as antecedent and/or consequents and therefore a non-monotonic inference engine is represented. This step is quite common in recent models using FCM [31]. In step 5 the rule base associated with the strategic decision level is included. Finally, step 6 corresponds to the model validation.

The FCM inference is made through concepts and their respective causal relationships. They are updated through iteration with the other concepts and with their own value. This is given by the matrix with the causal relations weights, and is represented by the weight sum, equation (1), similarly used in [27].. The values of the concepts evolve after the iterations, as shown by the function of equation (1) and (2) until they stabilize at a fixed point or in a limit cycle.

$$A_i = f(\sum_{\substack{j=1 \\ j \neq i}}^{n} (A_j \times W_{ji})) \tag{1}$$

where n is the number of nodes in the graph, Wji is the arc's weight that connects the concept Cj to Ci, Ai is the Ci concept value in the present iteration, and the f function (equation (2)) is a sigmoidal type function:

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{2}$$

The FCM, in some cases, may not stabilize and oscillate, or even exhibit chaotic behavior [32]. Generally, for well-behaved systems, it is observed that after a finite number of iterations, generally a low value, the FCM stabilizes, as shown in Fig. 3; for the FCM in this work it stabilize after 3 or 4 iterations. The concepts values reach a fixed equilibrium point or a limit cycle, presenting a small variation around a fixed value. In [26] it is analyzed the convergence of the FCM.

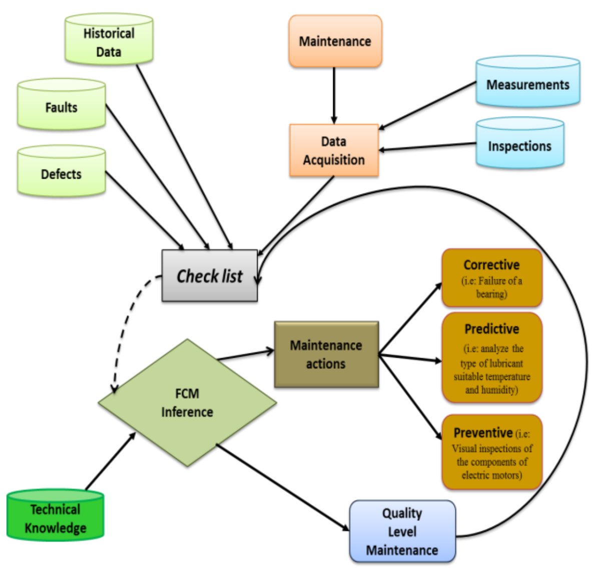

Figure 1. Maintenance management cognitive model.

Fig. 1 shows an overview of the decision-making sequence in which sDFCM is part of a maintenance strategy. It is observed that the FCM inference directly influences the decision-making, due to the reliability level found by the FCM. Also, according to Fig. 1, the check list processing determines the actions to be performed according to the maintenance information inputs. The initial propose of this research is to apply the same computational technique to different machines and / or equipment in the industry, such as electric motors and transformers. Thereby, it is intended to propose a generic soft-computing technique to contribute in the maintenance management area. It can be cited some papers that uses soft-computing techniques in maintenance management, ANN in [33] and in [20] it is used an FCM to assess the risks of maintenance outsourcing. Fuzzy Logic inference applied in maintenance management [34], and Mohammadreza's work [35] used Fuzzy Logic for strategy in maintenance management.

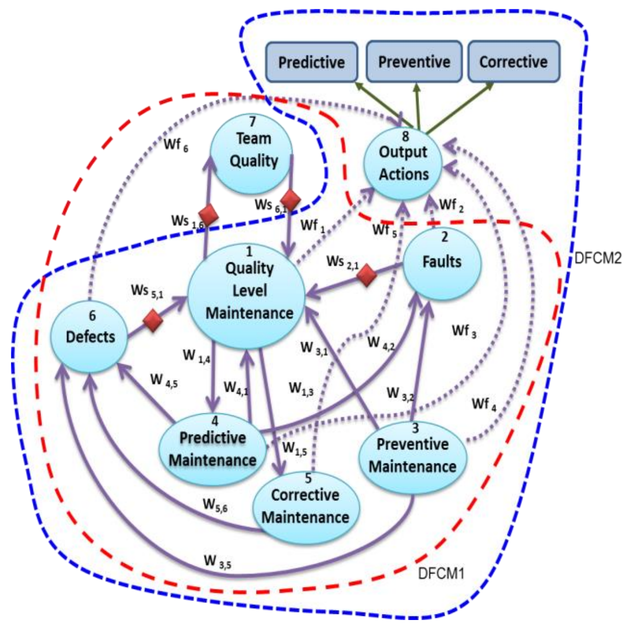

Figure 2. Complete sDFCM (sDFCM1 + sDFCM2)

An important aspect for this work is to characterize some of these properties come from measurements and are thus represented by real numbers. However, in many cases (such as this research), a large amount of information comes from expert estimates [36].

The complete sDFCM (Fig. 2) is divided in two parts to contemplate the cognitive model strategy presented in Fig. 1. The sDFCM1 (red dashed line) uses as input concepts the level of occurrence and quality of preventive and predictive maintenance. The established criteria are: when these levels are above 50% they have a positive influence in the reduction of the faults and defects, and consequently in the maintenance quality level; the maintenance quality level has a weak negative influence on the training and qualification of the team. Which suggests that when the maintenance level result is under the 50% criteria, it is needed a higher team qualification, and vice versa. The selection functions (represented by the red squares) are used for the inversion of the causality between the input concepts and the faults and defects occurrence associated with a rule or condition, in this case the threshold value of 50%. The discourse universe will be established by the maintenance policy.

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The sDFCM2 (blue dashed line) completes the proposed strategy with maintenance suggestions according to the input intensities of related concepts and the maintenance quality level from sDFCM1. The connections are fuzzy values obtained through the inference by a set of fuzzy rules. As example, if the maintenance quality level is high and the defects levels are low, the sDFCM2 may suggest preventive maintenance. In short, sDFCM changes its structure according to variations of the input concepts. As result, after the cognitive model development, the W matrix in the original definition reported in [9] is now a time varying matrix which values are computed per the importance (level) of the modeled characteristic and the relationship types. Each weight in this matrix can be also modeled as a tuple:

$$(N, C_i, C_o, r, U, B_r) \tag{3}$$

Where:

- N identifies the layer or level where the relationships belongs, i.e., a pure causal relationship have N = 0, since it belongs the lowest layer level.
- Ci represents the input concepts composing the inference premise.
- Co represents the output concepts of the relationship.
- r is the type of relationship, which can be a causal relation, a time varying causal relation, a fuzzy relation or a selection relation.
- U describes the universe of discourse of the relationship, which can be a numeric value, an interval or a linguistic variable.
- Br is the index representing the rule base relevant to the relationship, thus pure causal or time varying causal relation has Br = 0.

IV. Initial sDFCM Results

This section will present and discuss the initial sDFCM1 results. It is noteworthy that the results reached a limit cycle, due to small variations in the output, as can be seen in Figs. 3 and 4. This paper is a work in progress, thus a comparison of this approach with other methodologies such as classic Fuzzy will be implemented and presented in future papers.

The initial version of the sDFCM was simulated in two scenarios, one with favorable conditions and the other with unfavorable conditions. Fig. 3 shows the initial results for the favorable conditions, when it is provided to the sDFCM1 considerably high levels of corrective and predictive maintenance, in which the system infer maintenance quality level over 89%. It suggests that team training need gets lower, and consequently, tends to lower faults and defects occurrences.

On the other hand, when it is provided an unfavorable condition to the sDFCM (Fig. 4), the maintenance quality level lowers considerably to around 55%. It suggests a greater need of team training and higher possibility of fault and defects occurrence.

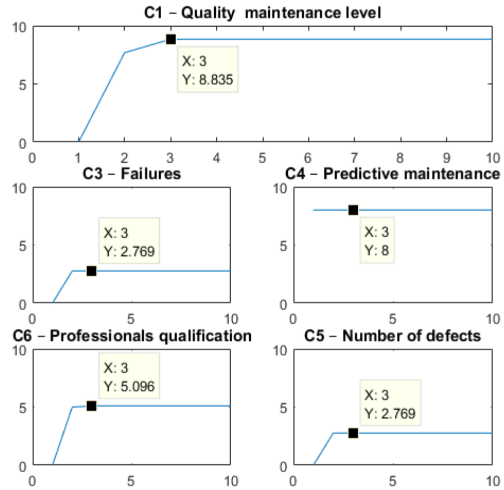

Figure 3. sDFCM initial results, favorable conditions.

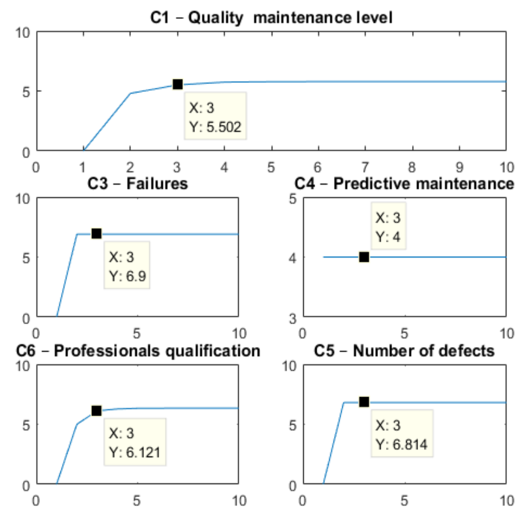

Figure 4. sDFCM initial results, unfavorable conditions.

V. Conclusions

According to the initial results, the sDFCM corresponded to the expectations of the work, assigning coherent quantitative values to the maintenance quality level in a favorable and unfavorable situation. The possibility levels of failures and defects occurrence were also coherent, as well the need for training and qualification of the team. Thus, to validate this tool, adjustments will be necessary in the model, which may occur according to different policies of each application.

It is expected to have contributed to maintenance management area and to Fuzzy Cognitive Maps models with a computational tool to provide a quantitative feedback for possible decision making through an initially qualitative knowledge-based model of the experts.

Future works will address a comparison of the computational complexity between sDFCM and DFCM, and the implementation of the sDFCM2. Finally, the application of the concepts presented in this research in a real case study to validate the sDFCM, as well the comparative with classic technique in the literature, such as classic Fuzzy.

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