SIMPLIFIED DYNAMIC FUZZY COGNITIVE MAPS APPLIED IN MAINTENANCE MANAGEMENT OF ELECTRIC TRANSFORMERS

MAPAS COGNITIVOS FUZZY DINÂMICOS SIMPLIFICADOS APLICADO À GESTÃO DE MANUTENÇÃO DE TRANSFORMADORES ELÉTRICOS

Data de entrega dos originais à redação em: 03/10/2017
e recebido para diagramação em: 04/12/2017

Patrick Prieto Soares [1] Lucas Botoni de Souza [2]
Ivan Rossato Chrun [3] Márcio Mendonça [4] Marco A. F. Finocchio [5]

The industry is composed by systems and machines that need to operate within suitable and defined parameters to ensure quality in its production line. Through maintenance management techniques such as Reliability-Centered Maintenance, it is intended to provide a quantitative feedback tool by means of Simplified Dynamic Fuzzy Cognitive Maps applied to electric transformers. This computational tool aims to provide a diagnosis with maintenance reliability levels assisting in future decision-making processes in maintenance management. This tool is based on failures and/or defects occurrence and team quality. This work aims at an initial development of a computational tool proposed by the authors.

Keywords: Maintenance Management. Reliability-Centered Maintenance. Electric Transformers. Fuzzy Logic. Simplified Dynamic Fuzzy Cognitive Maps.

1 INTRODUCTION

Transformers are essential components in energy distribution and industries (FINOCCHIO et al., 2016). The electrical transformers are divided into two classes characterized by its insulation type: the oil-type transformers, aim of this work, and the dry-type transformers. Those transformers have several applications as in energy generation, transmission, and distribution, in concessionaires, large industries and substations.

The importance of power transformers, in electrical systems, is directly linked to the electric power supply continuity. According Milanesi (2007), conceptually, the transformers are static electric machines. When the fault or defect occurs, the electric power supply is interrupted. Therefore, the electric power concessionaires are in the process of optimizing the maintenance and state's diagnostics of their substation equipment, especially power transformers, due their high cost of purchasing, repairing and replacing – which can reach millions of dollars (KULKARNI; KHAPARDE, 2012).

Making decisions is a common action people have to do every day throughout their lives. Even though it might seem as something trivial, the decision taken is a result of experiences, knowledge and one's ability to assess the situation. Depending on the problem, if a decision is taken by some expert in the subject, it has a higher chance to be the optimal, or at least successful, solution. To assist in the decision-making process, creating a graphic illustration to represent the problem is one of the possible ways to analyze it and reach a conclusion (ELENI; PETROS, 2017).

In this context, the need for maintenance management of these 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 in order to maintain its functionality, safety, and environmental characteristics. Otherwise, the maintenance must allow the equipment to operate in order to ensure 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. One of the known maintenance management strategies is the Reliability-Centered Maintenance (RCM) (SMITH, 1993; SAE, 2002), 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 (MOUBRAY, 2000).

Thus, the concepts of failure and structured analysis will be used in the development of this research. However, the proposed tool is in an initial stage, it can be extended and applied to transformers with different power specifications, from distribution ones to those applied in industries, such as from 45 KVA to 3 MVA.

1 - Departamento Acadêmico de Engenharia Elétrica, UTFPR - CP - Universidade Tecnológica Federal do Paraná, Campus Cornélio Procópio.
2 - Departamento Acadêmico de Engenharia Elétrica, UTFPR - CP - Universidade Tecnológica Federal do Paraná, Campus Cornélio Procópio.
3 - Departamento Acadêmico de Engenharia Elétrica, UTFPR - CP - Universidade Tecnológica Federal do Paraná, Campus Cornélio Procópio.
4 - Departamento Acadêmico de Engenharia Elétrica, UTFPR – CP - Centro Integrado de Pesquisa em Engenharia Mecânica Aplicada, CIPEMA, Campus Cornélio Procópio - Universidade Tecnológica Federal do Paraná, Campus Cornélio Procópio. < mmendoncautfpr@gmail.com >.
5 - Laboratório de Segurança Iluminação e Eficiência Energética (LABSIEE) - Universidade Tecnológica Federal do Paraná, Campus Cornélio Procópio.

The objective of this work is to build a structured model of a maintenance management system with two secondary objectives. Initially simulate and predict maintenance quality levels according to maintenance quality level, number of faults and defects recorded and team qualification. After the initial stage suggest actions necessary to improve the level of maintenance quality.

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

2 MAINTENANCE MANAGEMENT CONCEPTS

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 management of maintenance systems is a complex activity, especially when there are several contracting companies acting as executors of planned and emergency activities (HENRIQUES, 2016). In particular, the maintenance of electrical transformers, due to the need of uninterrupted supply and energy's quality.

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, as in the case of transformers, 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 the transformation and distribution of energy. In this context, the development of a strategy that indicates reliability levels can be used to help in the management of the maintenance, identifying possible points of improvements in the quality, e.g. the technical knowledge of the manpower.

It's not the scope of this work to discourse the types of maintenance, only to substantiate the concepts required for maintenance management inspired by the RCM technique by means of an sDFCM.

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

- Corrective Maintenance: performed when a failure occurs on 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's also identified as unplanned, where an unexpected failure occurs, 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 constant equipment monitoring through more sophisticated instruments, which allows an equipment's maintenance before a break happens and it stops working. Some of the main methods used to monitor equipment include vibration analysis, thermography analysis, oil analysis, noise analysis, among others.

Aiming the construction of a tool to assists in decision-making regarding failures and defects, especially of 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. Examples: overheating, excessive vibration, incipient electric shocks (in the initial stage), among others;
- 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 this work's purpose 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 (FRAZÉN; KARLSSON, 2007).

There are several maintenance management strategies in the literature (HOYLAND; RAUSAND, 2004). The RCM is a technique that is used to develop cost-efficiency maintenance plans and criteria so the equipment operational capability is achieved, restored, or maintained. The main objective of RCM 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 usually used, in maintenance management, for standardization and recording of sequence of the actions to be performed. The execution frequency establishment of the checklist 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 (FUKUZAWA et al., 2005). The priority regarding the activity to be developed in maintenance should also be determined. Which are stipulated according to the importance and nature of the machine. However, it is necessary to define its frequency of execution, using suitable models. A priori, suggestions of the main actions are presented, in a summarized way, adopted by the authors or specialists. Table 1 presents some observed concepts to this work's development, e.g., the transformer temperature measurement, an important factor when the former is operating on overload conditions.

Table 1 - Check List – Maintenance in oil type transformers

Item	Maintenance actions description
01	Inspection of the general state of conservation: cleaning, painting and metal parts corrosion.
02	Verification for leaks of insulating oil.
03	Verification of the conservation state of sealings.
04	Verification of insulating oil level in the main tank.
05	Verification of grounding in the main tank.
06	Check the operation of the gas relay, flow relay and the pressure release valve of the main tank.
07	Verification of the saturation state of the drying material used in the preservation of the insulating oil.
08	Verification of conservation status of conservative bags and membranes.
09	Verification of oil level and temperature indicators.
10	Checking the operation of the oil circulation system.
11	Verification of the cooling system.
12	Checking the oil level in the commutator compartment.
13	Inspection of wiring and interconnecting boxes.
14	Measurement of vibration and noise of fans and pumps of the cooling system.
15	Verification of the manual and automatic (if present) commutation system.
16	Inspection of the commutator motorized drive box.
17	Power factor and capacitance tests of the capacitive shunt bushings.
18	Reliability level found by the sDFCM.

In this context, 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. However, it is stressed that the insulation degradation is a major concern for these aged transformers around world (SAHA, 2003).

3 SIMPLIFIED DYNAMIC FUZZY COGNITIVE MAPS APPLIED TO MAINTENANCE QUALITY LEVEL

The need for monitoring in industrial electrical installations can be found in Paoletti and Herman (2015). In this context, this research suggests the use of a sDFCM, a variation of the classic FCM, to assign maintenance quality levels, the initial version of sDFCM1 implemented in this paper and its complete version (sDFCM1 and sDFCM2, in a future work), to assist decision making in the maintenance management area.

Since the pioneering work of Kosko (1986), which extended Cognitive Maps (AXELROD, 1976) by the inclusion of Fuzzy Logic, several applications of FCM have emerged in the literature in several knowledge areas.

Fuzzy Cognitive Maps (FCM) is composed by Axelrod's Cognitive Maps paper which causal relationships have fuzzy values attached to. They are system models in a graph-form, where the nodes are the concepts related to the problem, and the lines are the causal relationships. It is usually used to study system dynamics because of its mathematically simplicity. The relationship's influence is calculated using normalized state and matrix multiplications.

The inference may reach a steady state, a limit cycle or even a chaotic state. (KOSKO, 1986; TABER, 1994). The activation level of a concept is based on its previous iteration and the propagated weighted values of all other concepts.

There are many examples of FCMs that use monotonic and symmetric weight cause-effect relationships between the concepts in the literature. It might work on controlled environments but when it comes to the real world it can't be applied because of the dynamics aspects. A few techniques can be used to fix it, such as using Fuzzy rules and feedback mechanisms (CARVALHO; TOME, 2000) or algebraic equations to define the causal relationships when the real system have been modeled by crisp relations (AGUILAR, 2004).

Some applications of the FCM and its variations can be found in the literature in the areas of artificial life (DICKERSON; KOSKO, 1996; ARRUDA et al., 2016), spot detection in images generated by stereo camera systems (PAJARES; DE LA CRUZ, 2006), mobile robotics (PIPE, 2000), decision making in the medical field (PAPAGEORGIOU et al., 2012), time series prediction (HOMENDA; JASTRZEBSKA; PEDRYCZ, 2014), multi agent systems (RODIN et al., 2009; ACAMPORA; LOIA, 2011), process control (MENDONÇA et al., 2013), maintenance management (JAMSHIDI, 2015) among others.

Recently, some studies are using learning algorithms to adjust interaction weights among the factors to overcome the drawback in FCM (CHEN; CHIU, 2016). In this way, evolutions of the FCM has appeared, such as ED-FCM (Event-Driven - Fuzzy Cognitive Maps) applied in autonomous mobile robotics (MENDONÇA; ARRUDA; NEVES, 2011), and DCN (Dynamic Cognitive Networks) on process control (MIAO et al., 1999; MENDONÇA; ARRUDA, 2015). In Acampora and Loia (2011) is presented a formal adaptation of the original FCM, 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 (NÁPOLES, et al., 2016) 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 has been also noted, in short, FCMs are powerful tools for modeling dynamic systems. On the other hand, although FCM are considered as neural systems, there are important differences regarding other types of artificial neural networks (ANN).

Classical ANN models regularly perform like black boxes, where both neurons and connections do not have any clear specific meaning for the problem itself. However, all the neurons of the FCM have a precise meaning for the physical system and correspond to specific variables (NÁPOLES et al., 2016). In this way, according Rodin et al. (2009), 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 (YESIL et al., 2013). 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.

In specific case, used in this article, FCMs allow a quantitative analysis of the dynamic behavior in the FCM models to aid decision making. Thus, planners can reach the same response on viable combinations of input values for independent FCM variables and calculate dependent variables to assess the input variation's impact and alternative system description, like different solutions of a complex problem. In that way, this can be linked to a future state that is internally consistent due to it is the result of a calculation, which considers all direct and indirect relationships between the concepts (JETTER; KOK, 2014). In Section 4 will be presented some predictions of maintenance quality level. In addition, it is possible to make other predictions and analysis of different scenarios in order to plan management actions.

Further construction details of the classical FCM with different mathematical formalisms, inferences types and applications can be found in Glykas (2010). Recently, Papageorgiou (2014) 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 (LEE; LEE, 2015) is presented as development steps of an FCM model, as shown in Table 2.

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 sDFCM dynamic tuning machine learning algorithms not necessary. More information on the development of DFCM can be found in Arruda et al. (2016), 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 in the graph of fuzzy relations that model cause-effect relationships. 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 (PAPAGEORGIOU, 2012). In step 5 the rule base associated with the strategic decision level are 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 are represented by the weight sum, equation (1). The values of the concepts evolve after the iterations, as shown by the function of equation (1) in (2) until they stabilize at a fixed point or in a limit cycle.

$$A_i = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n} \left(A_j \times W_{ji}\right) + A_i^{previous}\right) \quad (1)$$

Where n is the number of nodes in the graph, W_{ji} is the arc weight that connects the concept C_j to C_i, A_i is the C_i concept value in the present iteration. Similarly, $A_i^{previous}$ is its C_i concept value in the previous iteration, and the f function (2) is a sigmoidal type function:

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

Table 2 - FCM Ontology

Steps	Description
01	Identification of elementary concepts, their roles (input, output, decision and level) and their interconnections, determining its causal nature (positive, negative, neutral).
02	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.
03	Determination of ontological influence among concepts. Design of the different ontological views of the system.
04	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.
05	Design of management level corresponding to the development of the rule base that are associated to and selection relations, and, implementation of algorithm to online learning such as reinforcement learning rules.
06	Model Validation.

The FCM, in some cases, may not stabilize and oscillate, or even exhibit chaotic behavior (STYLIOS; GROUMPOS, 1998).

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, stabilizing 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 Nápoles et al. (2016) it is analyzed the convergence of the FCM.

Figure 2 – Complete sDFCM

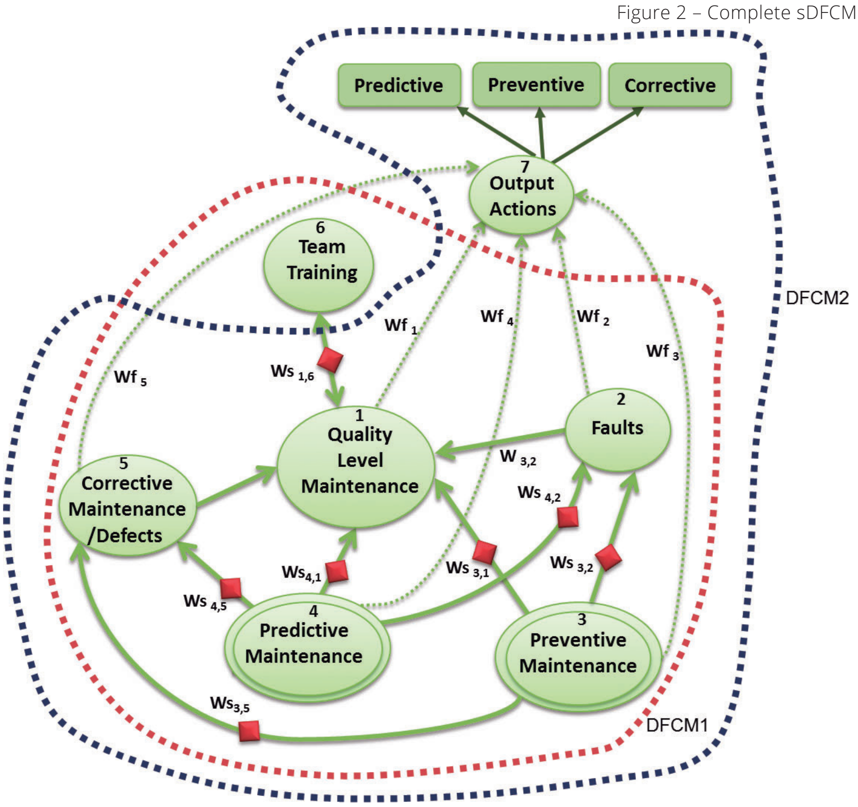
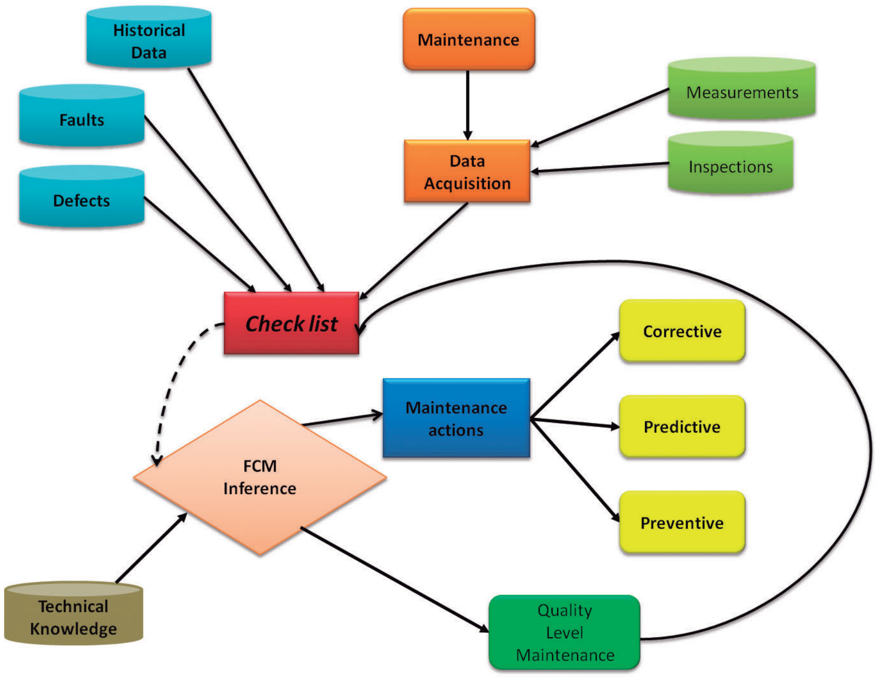


Fig. 1 shows an overview of the decision-making sequence, in which sDFCM is part of a maintenance strategy. It is observed that the FCM inference directly influences the decision making, due to the reliability level found by the FCM. Also, according to Fig. 1, the checklist item processing determines the actions to be performed according to the maintenance information inputs.

It can be cited some papers that uses soft-computing techniques in transformer or maintenance management, ANN in Finocchio et al. (2016), Fuzzy logic in Henriques (2016), and in Jamshidi (2015) it is used an FCM to assess the risks of maintenance outsourcing.

The complete sDFCM (Fig. 2) is divided in two parts to contemplate the whole 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.

Figure 1 - Maintenance management cognitive model



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 concepts associated with a rule or condition, in this case the threshold value of 50%. The discourse universe will be established by the maintenance policy.

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 type is 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 input concepts variations.

As result, after the cognitive model development, the W matrix in the original definition reported in Kosko (1986), is now a time varying matrix which values are computed according to the importance (level) of the modeled characteristic and the relationship types. Each weight in this matrix can be also modeled as a tuple:

$$(C_i, C_o, r, U, B_r)$$

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.

4 INITIAL sDFCM RESULTS

In this section will be presented and discussed the initial sDFCM1 results. It is noteworthy that the results reached a limit cycle, due small variations in the output, as can be seen in Fig. 3, 4 and 5.

The sDFCM was simulated in three scenarios, one with favorable conditions, the second with average conditions, and the other one 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 86%. It suggests that team training needs gets lower, and consequently, tends to lower faults and defects occurrences.

Figure 3 – sDFCM initial results, best scenario

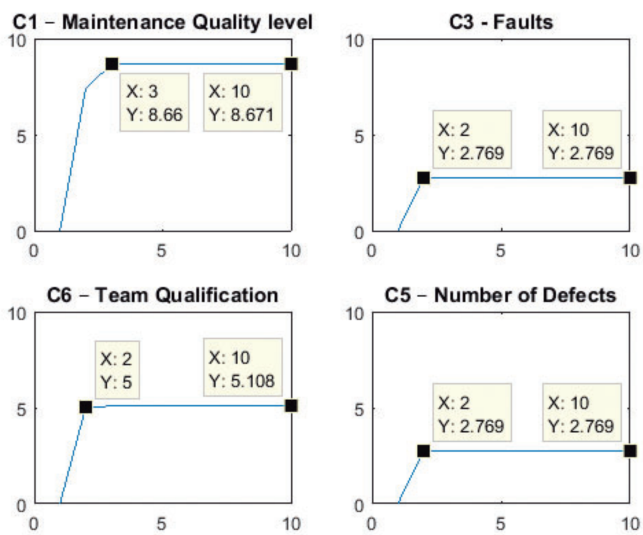


Figure 4 – sDFCM initial results, average scenario

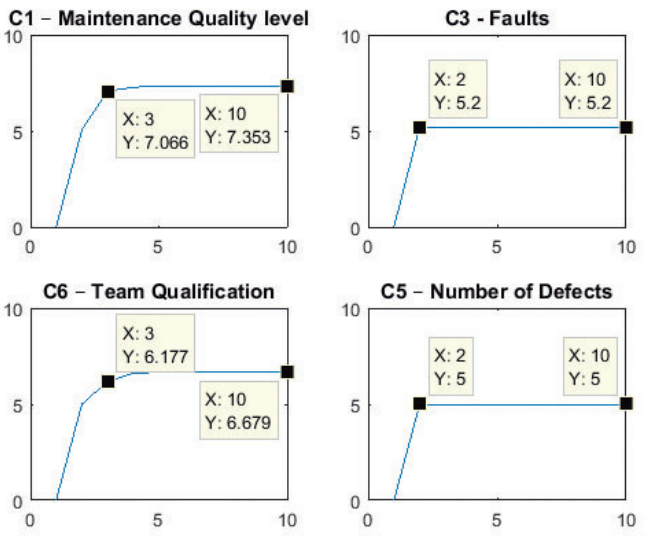
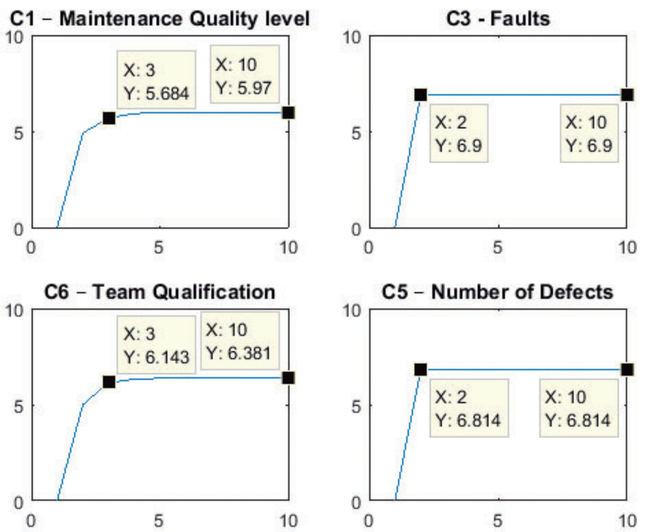


Figure 5 – sDFCM initial results, worst scenario



On the other hand, when it is provided an unfavorable condition to the sDFCM (Fig. 5), the maintenance quality level lowers considerably. In which the inputs are close to 40%, resulting in, approximately, a maintenance quality level of about 57%.

As can be seen in the Fig. 5, due the low maintenance quality level, the sDFCM suggests a greater need of team training and higher possibility of fault and defects occurrence.

To verify the results from both best and worst conditions, an average conditions set was made, as seen on Fig. 4. As expected, this case presented numbers between the two other scenarios, with a maintenance quality level at about 70% (above best case), and lower number of defects than the worst scenario.

It can be noticed that the diagnosis of maintenance quality level was sensitive to the different cases, decreasing with the increased number of defects and failures detected. In this way, some predictions of the maintenance level of different scenarios can be made. For example, one can try to predict the maintenance quality level by reducing the number of failures and defects.

5 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 hoped 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. The initial version of the sDFCM1 tool can provide quality level predictions for future maintenance management actions.

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

REFERENCES

ACAMPORA, G.; LOIA, V. On the Temporal Granularity in Fuzzy Cognitive Maps. **IEEE Transaction on Fuzzy Systems**, v. 19, n. 6, 2011.

AGUILAR, J. Dynamic random Fuzzy cognitive maps. **Computación y Sistemas**, v. 7, n. 4, 2004.

ARRUDA, L. V. R.; MENDONÇA, M.; NEVES, F.; CHRUN, I. R.; PAPAGEORGIOU E. I. Artificial life enviroment modeled by dynamic fuzzy cognitive maps. **IEEE Transactions on Cognitive and Developmental Systems**, 2016.

AXELROD, R. **Structure of Decision:** The Cognitive Maps of Political Elites." Princeton, NJ: Princeton Univ. Press, 1976.

CARVALHO, J. P.; TOME, J. A. Rule based Fuzzy cognitive maps-qualitative systems dynamics. In: Proceedings 19th International Conference of the North America. **Fuzzy Information Fuzzy Processing Society**, 2000.

CHEN, C. T.; CHIU, Y. T. **A study of fuzzy cognitive map model with dynamic adjustment method for the interaction weights**," 2016 International Conference on Advanced Materials for Science and Engineering (ICAMSE), Tainan, Taiwan, 2016.

DICKERSON, J. A.; KOSKO, B. Virtual worlds as Fuzzy dynamical systems. In: SHEU, B. (Ed.) Technology for multimedia, **New York: IEEE Press**, 1996.

ELENI, V.; PETROS, G. **New concerns on fuzzy cognitive maps equation and sigmoid function**, 2017. 25th Mediterranean Conference on Control and Automation (MED), Valletta, Malta, 2017, pp. 1113-1118.

FINOCCHIO, M. A. F.; LOPES, J. J.; DE FRAÇA, J. A.; PIAI, J. C.; MANGILI J. F. **Neural networks applied to the design of dry-type transformers:** an example to analyze the winding temperature and elevate the thermal quality. Int. Trans. Electr. Energ. Syst, 2016.

FRANZÉN, A.; KARLSSON, S. **Failure Modes and Effects Analysis of Transformers**. Master thesis, Royal Institute of Technology, KTH, 2007.

FUKUZAWA, T.; YAMAMOTO, M.; HATA, T.; ASAOKA, K.; AIZAWA, M. Implementation of Product Assessment in a Generic Mechanical Parts Manufacturer. **4th International Symposium on Environmentally Conscious Design and Inverse Manufacturing,** Tokyo, 2005.

GLYKAS, M. Fuzzy **Cognitive Maps Advances in Theory, Methodologies. Tools and Applications.** Greece Springer, 2010.

HENRIQUES, H. O., et al., Fuzzy Inference Method Applied to Georeferenced Maintenance Management. in **IEEE Latin America Transactions**, vol. 14, nº. 9, pp. 4043-4047, 2016.

HOMENDA, W.; JASTRZEBSKA, A.; PEDRYCZ, W. Modeling time series with fuzzy cognitive maps. In Fuzzy Systems (FUZZ-IEEE), 2014. **IEEE International Conference on**, pp, 2055-2062, 2014.

HØYLAND, A.; RAUSAND, M. **System Reliability Theory, Models, Statistical Methods and Applications.** Jhon Wiley and Sons, second edition, 2004.

JAMSHIDI, A. Dynamic risk modeling and assessing in maintenance outsourcing with FCM. Industrial Engineering and Systems Management (IESM), 2015. **International Conference**, 2015.

JETTER, A. J.; KOK, K. Fuzzy Cognitive Maps for futures studies— A methodological assessment of concepts and methods, In **Futures,** Volume 61, Pag 45-57, ISSN 0016-3287.

Kosko, B. (1986). **Fuzzy Cognitive Maps**, Int. J. Man-Machine Studies, 2014.

KULKARNI, S. V.; KHAPARDE S. A. **Transformer Engineering:** Design, Technology, and Diagnostics. CRC PRESS, Second Edition, 2012.

LEE, D. H. AND LEE, H. **Construction of holistic fuzzy cognitive maps using ontology-matching method.** Expert Systems with Applications, 2015.

MENDONÇA, M.; ANGELICO, B.; ARRUDA, L. V. R.; NEVES JR, F. A dynamic fuzzy cognitive map applied to chemical process supervision. **Engineering Applications of Artificial Intelligence,** v. 26, n. 4, p. 1199-1210, 2013.

MENDONÇA, M.; ARRUDA, L. V. R.; NEVES JR, F. Autonomous navigation system using event driven-fuzzy cognitive maps. **Springer Science+Business Media**, 2011.

MENDONÇA, M.; ARRUDA, L. V. R. **A Contribution to the Intelligent Systems Development Using DCN.** OmniScriptum GmbH & Co. KG, 2015.

MIAO, Y.; ZHI-QIANG, L.; SHI, L.; SIEW, C. K. Dynamical cognitive network-an extension of fuzzy cognitive map," Tools with Artificial

Intelligence, Proceedings. 11th **IEEE International Conference** on, Chicago, IL, 1999.

MILANESI, F. **Trasformatori Elettrici**. LULU PRESS: Milano, 2007.

MOUBRAY, J. **Reliability Centered Maintenance.** Lutterworth, England, 2nd Edition, Aladon Ltd, 2000.

NÁPOLES, G.; PAPAGEORGIOU, E. I.; BELLO, R.; VANHOOF, K. **On the onvergence of sigmoid fuzzy cognitive maps.** Information Sciences, Elsevier, 2016.

PAOLETTI, G. J.; HERMAN, G. Striving for Zero Panned Outages: Monitoring Electrical Equipment Failure Indicators," In: **Industry Applications Magazine**, IEEE, 2015.

PAJARES, G.; DE LA CRUZ, J. M. Fuzzy cognitive maps for stereovision matching. **Pattern Recognition**, v. 39, n. 11, 2006.

PAPAGEORGIOU, E. I.; ROO, J. D.; HUSZKA, C.; COLAERT, D. Formalization of treatment guidelines using Fuzzy Cognitive Mapping and semantic web tools," **Journal of Biomedical Informatics**, vol. 45 nº.1, pp. 45-60, 2012.

PAPAGEORGIOU, E. I. **Learning algorithms for fuzzy cognitive maps**: A review study," IEEE Trans. Syst., Man Cybern. C Appl. Rev, 2012.

PAPAGEORGIOU, E. I. **Fuzzy Cognitive Maps for Applied Sciences and Engineering From Fundamentals to Extensions and Learning Algorithms.** Springer-Verlag Berlin Heidelberg, 2014.

PIPE, A. G. An architecture for building "potential field" cognitive maps in mobile robot navigation. **Adaptive Behavior**, v. 8, n. 2, p. 173-203, 2000.

RODIN, V., et al. Multi-Agents System to Model Cell Signalling by Using Fuzzy Cognitive Maps. Application to Computer Simulation of Multiple Myeloma. 2009 Ninth **IEEE International Conference on Bioinformatics and BioEngineering**, Taichung, 2009.

SAE International. SAE JA1012: A Guide to the Reliability-Centered Maintenance (RCM) Standard. Warrendale, USA, **SAE Publication**, 2012.

SAHA, T. K. Review of modern diagnostic techniques for assessing insulation condition in aged transformers," in **IEEE Transactions on Dielectrics and Electrical Insulation**, 2003.

SMITH, A. M. **Reliability-Centered Maintenance.** McGraw-Hill, New York, 1993.

STYLIOS, C. D. AND GROUMPOS, P. P. (1998). The challenge of modeling supervisory systems using fuzzy cognitive maps. **Journal of Intelligent Manufacturing**.

TABER, R. **Fuzzy cognitive maps model social systems**. AI Expert, 1994.

YESIL, E.; OZTURK, C.; DODURKA, M. F. AND. SAKALLI, A. Fuzzy cognitive maps learning using Artificial Bee Colony Optimization," Fuzzy Systems (FUZZ), **IEEE International Conference on, Hyderabad**, 2013.