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Fuzzy Grey Cognitive Maps in reliability engineering

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ABSTRACT

Current industrial equipment has become more complex and huge. In this case, the conventional reliability techniques cannot correctly support functional assessment. This paper integrates an innovative soft computing methodology, Fuzzy Grey Cognitive Map (FGCM), into a traditional reliability analysis for better knowledge. FGCMs are used for evaluating, modelling and aiding decision-making by examining causal relations among relevant domain concepts. The proposed procedure is illustrated with a reliability analysis of a transformer active part. Twenty failure causes in the transformer's active part are identified and assessed. In addition, six failure scenarios are simulated. The results revealed the potential of the combination of FGCM and failure analysis for complex systems. The proposed methodology exposes the potential benefits it could provide in order to assist electric power system decision-makers to supply its customer electrical energy with a high degree of reliability.

1. Introduction

Nowadays, different engineering techniques can be used to support reliability, maintainability, testability and safety analysis. Reliability is one of the most valuable quality characteristics of components, products, and large and complex systems. Consumers require from the manufacturing industry and service industry the reliability of products and services. In this regard, a complete knowledge of the system or process behaviour leads to significant increase of the reliability level.

Failure analysis and reliability are essential functions to all of the engineering disciplines. The application of these two functions improves the reliability operational assessment of a system or process.

The modelling of complex systems requires new methods and techniques that can utilize the existing knowledge and human experience [27,33]. Furthermore, these methods should be equipped with sophisticated features such as failure detection, optimization and identification qualities.

In this research, the soft computing methodology of Fuzzy Grey Cognitive Map (FGCM) is proposed for modelling complex systems. The objective of this work is to introduce the advantages and potential use of Fuzzy Grey Cognitive Maps (FGCMs) in modelling complex systems and to prove how appropriate FGCMs are used to exploit the knowledge and experience of experts on the description and modelling of the complex systems failures.

FGCM represents knowledge, uncertainty and relates states, variables, events, inputs and outputs in an analogous way to that of human beings.

This paper focuses on methods in reliability engineering from the point of a new perspective based on FGCM. This novel technique offers an excellent mechanism to support decision-making [28]. The provided method is applied to a subsystem of a transformer which is considered a reparable system, i.e. the transformer active part. The combination of FGCM with failure analysis may offer a practical methodology for carrying out distribution system reliability evaluations.

This paper is structured into five sections. The second section shows briefly the Grey Systems Theory fundamentals. The third section describes the FGCM model and its characteristics. The fourth section presents a real case study to demonstrate the potential applications of the proposed methodology. Conclusions are drawn in section five.

2. Grey Systems Theory

Grey Systems Theory (GST) has become a very effective set of solving problem techniques within environments with high uncertainty, under discrete small and incomplete data sets [9]. GST has been designed to analyse small data samples with poor information, with successful applications in energy, transportation, meteorology, medicine, industry, military science, business, agriculture, geology, and so on.

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According to the degree of known information, if the system information is fully known (whole understanding), the system is called a white system, while the system information completely unknown is called a black system. A system with partial information known and partial information unknown is called grey system.

GST contemplates the information fuzziness, because it can flexibly deal with it [16,17,34]. Furthermore, fuzzy mathematics holds some previous information (usually based on experience); while grey systems deal with objective data, they do not require any additional information other than the data sets that need to be disposed [37]. Moreover, GST fits better with multiple meanings (grey) environments than fuzzy logic.

Let U be the universal set. Then a grey set $\mathbf{G} \in U$ is defined by its both mappings. Note that

$$\mathbf{G} = \begin{cases} \overline{\mu}_G(x): & x \rightarrow [0, 1] \\ \underline{\mu}_G(x): & x \rightarrow [0, 1] \end{cases} \tag{1}$$

where $\underline{\mu}_G(x)$ is the lower membership function, $\overline{\mu}_G(x)$ is the upper one and $\underline{\mu}_G(x) \leq \overline{\mu}_G(x)$. Also, GST extends fuzzy logic, since the grey set $\mathbf{G}$ becomes a fuzzy set when $\underline{\mu}_G(x) = \overline{\mu}_G(x)$.

The accurate value of a grey number is unknown, but it is known that the range within the value is included. We denote an interval grey number as $\otimes G$, and it is a grey number with both a lower limit ($\underline{G}$) and an upper limit which is called an interval grey number [17], and it is denoted as $\otimes G \in [\underline{G}, \overline{G}] | \underline{G} \leq \overline{G}$. Both limits are fixed numbers in first order interval grey numbers. If the grey number $\otimes G$ has only lower limit, it is denoted as $\otimes G \in [\underline{G}, +\infty)$, and if it has only upper limit, it is denoted as $\otimes G \in (-\infty, \overline{G}]$.

A black number would be $\otimes G \in (-\infty, +\infty)$, and a white number is $\otimes G \in [\underline{G}, \overline{G}]$, $\underline{G} = \overline{G}$. We have no information about black numbers and we have the complete information about white numbers.

The transformation process of grey numbers in white ones is called whitenization [17], and the whitenization value is calculated as follows

$$\hat{\otimes} G = \alpha \cdot \underline{G} + (1 - \alpha) \cdot \overline{G} | \alpha \in [0, 1] \tag{2}$$

when $\alpha = 0.5$ is equal mean whitenization.

Moreover, we define the length of a grey number as $\ell(\otimes G) = |\underline{G} - \overline{G}|$. In that sense, if the length of the grey number is zero ($\ell(\otimes G) = 0$), it is a white number. In other sense, if $\ell(\otimes G) = \infty$, the grey number is not necessarily a black number, because the length of a grey number with only one limit (lower or upper), $\otimes G \in [\underline{G}, +\infty)$ or $\otimes G \in (-\infty, \overline{G}]$, is infinite but it is not a black number.

A more detailed explanation of grey numbers operations and FGCMs can be found in [28].

3. Fuzzy Grey Cognitive Maps

Most real-life decision-making processes are dynamic. Critical decisions in areas such as manufacturing, engineering, medicine, industry, marketing, finance, and other domains require multiple and interrelated time-constrained decisions within strongly uncertain and so complex environments [29,30].

Recently, Fuzzy Grey Cognitive Maps have been proposed as a FCM extension [28]. FGCM is based on GST, that it has become a very worthy theory for solving problems within domains with high uncertainty, under discrete small and incomplete data sets.

Furthermore, FGCMs provide an intuitive, yet precise way of expressing concepts and reasoning about them at their natural level of abstraction. By transforming decision modelling into causal graphs, decision makers with no technical background can understand all of the components in a given situation. In addition, with a FGCM, it is possible to identify and consider the most relevant factor that seems to affect the expected target variable.

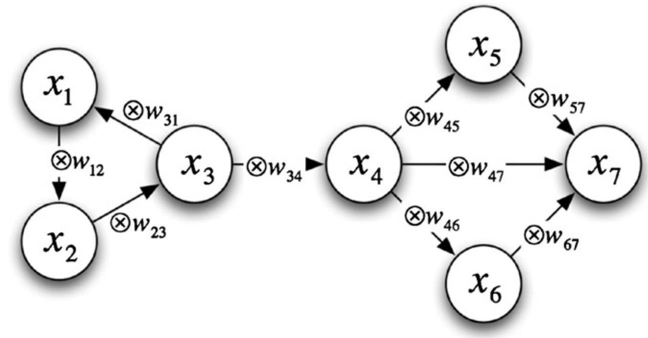

Fig. 1. Fuzzy Grey Cognitive Map example.

In addition, FGCM tools for practitioners, as the proposal of Xirogiannis and Glykas [38], could help for wide understanding of FGCMs as decision support tools.

3.1. Foundations

Fuzzy Grey Cognitive Map is an innovative soft computing technique. FGCMs are dynamical systems involving feedback, where the effect of change in a node may affect other nodes, which in turn can affect the node initiating the change [28]. A FGCM models unstructured knowledge through causalities through imprecise concepts and grey relationships between them based on FCM [14,15].

The FGCM nodes are variables, representing concepts. The relationships between nodes are represented by directed edges. An edge linking two nodes models the grey causal influence of the causal variable on the effect variable.

Since FGCMs are hybrid methods mixing grey systems and neural networks, each cause is measured by its grey intensity as

$$\otimes w_{ij} \in [\underline{w}_{ij}, \overline{w}_{ij}] | \underline{w}_{ij} \leq \overline{w}_{ij}, \{\underline{w}_{ij}, \overline{w}_{ij}\} \in [-1, +1] \tag{3}$$

where i is the pre-synaptic (cause) node and j is the post-synaptic (effect) one. Fig. 1 shows a FGCM graphical model example.

3.2. FGCM dynamics

FGCM dynamics begins with the design of the initial grey vector state $\otimes \vec{C}^0$, which represents a proposed initial grey stimuli. We denote the initial grey vector state with n nodes as

$$\otimes \vec{C}^0 = (\otimes C_1^0 \quad \otimes C_2^0 \quad \dots \quad \otimes C_n^0) = ([\underline{C}_1^0, \overline{C}_1^0] \quad [\underline{C}_2^0, \overline{C}_2^0] \quad \dots \quad [\underline{C}_n^0, \overline{C}_n^0]) \tag{4}$$

The updated nodes' states [28] are computed in an iterative inference process with an activation function, which maps monotonically the grey node value into its normalized range [0, +1] or [−1, +1]. Each single node would be updated with Eq. (5).

$$\begin{aligned} \otimes C_j^{t+1} &= f\left(\otimes C_j^t + \sum_{\substack{i=1 \\ j \neq i}}^{N} w_{ij} \cdot \otimes C_i^t \right) \\ &= f(\otimes C^{t*}) \\ &= f([\underline{C}^{t*}, \overline{C}^{t*}]) \\ &= [f(\underline{C}^{t*}), f(\overline{C}^{t*})] \\ &= [\underline{C}^{t+1}, \overline{C}^{t+1}] \end{aligned} \tag{5}$$

The unipolar sigmoid function is the most used one [7] in FCM and FGCM when the concept value maps in the range [0, 1]. If $f(\cdot)$