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Causal effect analysis for fuzzy cognitive maps designed with non-singleton fuzzy numbers

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ABSTRACT

In this study, a new static analysis approach is proposed for enhanced Fuzzy Cognitive Maps (FCMs), which have non-singleton fuzzy numbers in casual relation strength representation. Cognitive Maps (CMs) are proposed as a type of directed graph that offers a means to model interrelationships or causalities among concepts, and have a clear way to visually represent them. They graphically describe a system in terms of concepts, and causal beliefs, and are powerful graphical tools to represent knowledge of the experts. Fuzzy cognitive maps, which are weighted cognitive maps, are proposed also as graphical modelling technique that follows a reasoning approach similar to processes of human reasoning and human decision-making. In FCMs, the casual relations and its strengths are assigned in a unit interval with a sign. The assigned casual strengths in conventional FCMs are singleton fuzzy (crisp) numbers, and only allow to interpret the effects linguistically but do not represent the uncertainty or ambiguity in causality. In this paper, a new analysis is presented for finding the indirect effects and total effects between the concepts of enhanced FCMs that are represented with non-singleton fuzzy numbers, especially for triangular or trapezoidal fuzzy numbers. Firstly, the mathematical approach about fuzzy numbers and the proposed analysis is presented, then secondly an experimental study on modelling ERP maintenance risks via FCM is presented. The results of the proposed causal effect analysis are discussed for this model and the outcomes are compared with a conventional FCM model where the casual strengths are singleton fuzzy numbers. The results of the experiment show the benefit of using triangular fuzzy numbers when a group of experts are involved in modelling. The uncertainty and varieties between the experts' knowledge are easily captured and the casual effect between the concepts are successfully shown with the presented static analysis.

1. Introduction

Cognitive Maps (CMs) were proposed and applied to ill-structured problems by Political scientist Robert Axelrod [1] in the 1970s. CMs, which are signed digraphs, capture the causal assertions of an expert with respect to a certain domain, and then use these assertions in order to analyze the effects of alternative believes or causes upon certain goals. A CM basically has only two basic types of elements, which are concepts and causal beliefs. The concepts are represented as variables and the causal beliefs as relationships among variables. CMs allow variables to be continuous, ordinal, or dichotomous [2]. Causal relationships link these concepts to each other and they can be either positive or negative. Concepts that cause a change are called cause concept, while those that undergo the effect of the change in the cause variable are called effect concepts. If the relationship is positive, an increase or decrease in a cause concept, causes the effect concept to change in the same direction. On the contrary, if the relationship is negative, then the change which the effect variable undergoes is in the opposite direction.

In the graphical representation of a CM, the concepts are represented as nodes, and edges are causal connections. A path between two concepts in a CM is a sequence of all the nodes which are connected by an edge from the first node to the second node, another edge from the second node to the third and so on, until there is an edge from the next to the last node of the path [1]. In [1], the functional and weighted CMs are distinguished from the signed digraphs described above. A signed digraph allows for a sign to be assigned on each relationship thus modelling just the direction of the change. The sign can be replaced with positive or negative numbers which show not only the direction, but also the magnitude of the change. Such maps are called weighted cognitive maps. A specific function can also be assigned to each causal relationship in order to represent more accurately the direction and

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magnitude of the change. Such maps are called functional cognitive maps. As expected, the weighted and the functional CMs are more detailed and information rich than the signed CMs.

In 1986, Kosko introduced Fuzzy Cognitive Maps (FCMs), which are weighted cognitive maps with singleton fuzzy numbers [3]. As a CM, a Fuzzy Cognitive Map (FCM) is a graphical representation consisting of nodes indicating the most relevant factors of a decisional environment; and links between these nodes representing the relationships between those factors [4]. A FCM is a soft computing technique mostly used as a modelling methodology for complex decision systems, which has originated from the combination of fuzzy sets and neural networks.

For the construction of FCMs, experts of the specific domain problem develop a mental model manually based on their knowledge in related area. At the first stage, they identify key domain issues or concepts. Secondly, they identify the positive or negative causal relationship among these concepts, and as the last stage, they estimate causal relationships strength as the fuzzy singleton numbers [5,6]. Different approaches were proposed for the specification of the weights in a FCM. One suggestion is to ask the experts to assign a real number, which is a singleton fuzzy number, from the interval (0, 1] for each relationship and then calculate the average. It is expressed by some researchers that it is sometimes difficult for the experts to assign a real number in order to express their beliefs with regard to the strength of relationships, hence partially ordered linguistic variables such as *weak* < *moderate* < *strong* are preferred instead of a real number [3,7]. In the second case, all the values suggested by experts are considered as linguistic variables, and an overall linguistic weight is obtained, which is transformed to a numerical weight with the defuzzification method of Centre of Gravity [5].

There are two distinct methods for analyzing a given CM or FCM which has been developed to represent a given domain with the objective of using it for decision support. A static analysis can be used for establishing the relative importance of concepts, and indirect and total causal effects between nodes as mentioned in [1,8]. In a CM, the indirect effect of one concept on another concept over the path is negative if the number of negative signs (of the casual links) is odd, and positive otherwise. The total effect of one concept on the other concept would then be derived from the indirect effects over all possible paths. The total effect is negative if all the indirect effects are negative, it is positive if all the indirect effects are positive, and indeterminate otherwise [1]. In most real-world applications beyond a trivial level of complexity, the indeterminate case is the most frequent one. This problem can be solved by assigning numbers to the casual links, thereby creating a weighted digraph, so it is clear that FCM eliminate the indeterminacy problem of the total effect. The dynamic analysis of an FCM can be carried out to observe and explore the impact of changes in the decision domain with time. Given a FCM's connection matrix and an input stimulus in the form of a state vector, the resulting state can provide useful insights into the likely impacts of any changes made to the system modelled by the FCM. These changes may be made to provide an answer to a “what-if” question [8].

FCMs have been mostly used for planning and decision making in the fields of international relations, social systems modelling and the study of political developments in the context of such systems. Moreover, as mentioned in [9], there is a vast interest in FCMs and this interest on the part of researchers and industry is increasing, especially in the areas of control [10], business [11], medicine [12], robotics [13], emotion modelling [14], environmental science [15], education [16], information technology [17] and self-tuning controller design [18]. Even though FCMs have achieved success in many fields, there are some limitations inherent in FCMs, such as a lack of adequate capability to handle uncertain information or to aggregate information from different sources. Because of these deficiencies, several extensions have been proposed [19–23]. Mostly, the aim of these extensions is to bring more values to concepts including real-valued concepts, non-linear weight, and time delays. Moreover, several researchers investigate on automated FCM modelling using the data of the variable via new learning algorithms [24–27].

Recently, four novel studies extended the theory and the application of FCMs. In [28], a FCM extension, called Fuzzy Grey Cognitive Maps (FGCMs), has been proposed as an extension of the FCMs for environments with high uncertainty, under discrete small and incomplete data sets. In [29], an extension of the FCM that involves a factor of hesitancy into the weights of a standard FCM is presented. This is achieved by representing the causal relations with intuitionistic instead of conventional fuzzy sets, and by a suitably modified reasoning algorithm. In [30], a FCM and evidential theory is combined and the concept of evidential cognitive maps, which improves the ability to represent uncertainty and also the way of aggregating knowledge from different sources, is proposed. Finally, in [31] it is suggested to use Triangular Fuzzy Numbers (TFNs) in causal relationships between the concepts instead of fuzzy singletons to cope efficiently with uncertainty.

The FCM structure proposed by Kosko [3] allows signed weights which can be interpreted as fuzzy singletons. Even though these weights have a value within (0, 1] and represent the causal relationship strength, they are crisp real numbers and do not represent uncertainty and ambiguity. Especially, when a group of experts are involved in the FCM modelling, the finally obtained FCM loses the different perspectives of the experts by averaging the weights to a single number. As seen, using the fuzzy singletons in the defined interval excludes the diversity of expert knowledge representation. Therefore, using fuzzy numbers as stated in [31,32] will lead to more specified and information rich FCMs than the conventional FCMs.

In this study, a new causal effect analysis of the Fuzzy Cognitive Maps, which has the casual effects defined with triangular and trapezoidal fuzzy numbers, is studied. By the help of this FCM representation, the indirect and total effect of one concept to another will be signified more properly and the information will include the uncertainty of the experts' knowledge. Therefore, this paper firstly shows how to use non-singleton fuzzy numbers like triangular fuzzy numbers for FCM models, secondly how to calculate the indirect and total effects, as a part of the static analysis of a given enhanced FCM. An experimental analysis is conducted on the ERP maintenance risks FCM model, which is acquired from a group of experts, and for the experiments MATLAB is used to develop necessary codes.

Section II will present a brief overview of conventional CMs and FCMs. Section III will present the proposed causal effect analysis for FCMs represented via non-singleton fuzzy numbers, and introduce the extended mathematical background. Section IV will present an experimental study, which is used to show the proposed methodology and the benefit of the approach, and finally, Section VI will present the conclusions and future work.

2. From cognitive maps to fuzzy cognitive maps

Robert Axelrod [1] introduced CMs as a formal means of modelling decision making in social and political systems. CMs are a type of directed graph that offers a means to model interrelationships or causalities among concepts, and have a clear way to visually represent causal relationships. Moreover, they expand the range of complexity that can be managed, allow users to rapidly compare their mental models with reality, make evaluations easier, and promote new ways of thinking about the issue being evaluated [33].

CMs graphically describe a system in terms of concepts, and causal beliefs as given in Fig. 1 [4]. The nodes represent concept variables C_x, where $x = 1,2, \ldots, N$, and a concept variable at the origin of an arc (or edge) is a cause variable, whereas a concept variable at the endpoint of an arc is an effect variable. In [1], the indirect and total cause effects on CMs are introduced. A causal path in a given CM from concept C_i to concept C_j, for example $C_i \rightarrow C_{k_1} \rightarrow \ldots \rightarrow C_{k_n} \rightarrow C_j$ can be denoted with ordered indices as $(i,k_1,\ldots,k_n,j)$. Thus, the indirect effect from the