Intelligent Modeling and Decision Making for Product Quality of Manufacturing System Based on Fuzzy Cognitive Map

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Abstract

Recent research finds that consumers pay more and more attention to the high grade product. An intelligent decision making system is proposed in this paper, the purpose of which is to monitor product quality of manufacturing system and give warnings to the quality managers accordingly. Since the complex interaction among the multivariate quality characteristic (QC) and the intelligent model is hard to be manually managed, the well-performing machine learning algorithms need to be proposed to support an automatic control of product quality. And many decision making tools have been developed to monitor product quality with the intelligent control model. Fuzzy cognitive map (FCM) is a popular tool for intelligent modeling, and is usually applied to many fields. In this paper, FCM is used for intelligent modeling in the decision making process of manufacturing system. Based on the mechanism, we design an intelligent model to solve the decision making problem of product quality control. Then, the effect of varying the support scale of trained data is tested by using FCM in different environments. Finally, we get some useful conclusions and discuss several potential research developments in the future.

Keywords: *Product Quality, Intelligent Modeling, Decision Making, Manufacturing System, Fuzzy Cognitive Map*

1. Introduction

In recent decades, the intelligent modeling and decision making method has attracted considerable attention from different fields of scientific research and technological experimentation. The intelligent modeling approaches have become increasingly available for use in product quality decision making related research [1, 2]. On the other hand, as the global market becomes more and more competitive, consumers become more discriminating product quality [3]. So the fierce market competition has certainly made it easier for consumers to search for a high quality product [4, 5]. In fact, consumers often make a decision on product quality based on the QCs that the products have [6]. In order to improve product quality, a specific attention has to be paid to modeling intelligent system [7].

In a word, the intelligent modeling is one of the most important factors which can influence product quality [8]. And the conventional wisdom is that intelligent modeling has been a boon to decision makers. Furthermore, the intelligent modeling is a powerful technology and complete facility to support decision making process [9]. In more recent years, a lot of intelligent systems based on different machine learning models have been intensively applied in many areas [10]. With the development of the internet and computer technology, intelligent modeling techniques for their utilization to decision making problems have been investigated [11, 12]. Due to the rapid growth of computer network and intelligence technologies, the product quality is increasingly being controlled in decision making system [13]. Besides, the product quality monitoring of manufacturing system can provide a powerful tool for advanced warning for quality supervisors in decision making process [14].

Quality managers often rely on prior knowledge during decision making tasks due to information processing limitations. While saving time and costs have been mentioned as the primary drivers of decision making, saving time may be more important than saving costs for most quality managers of enterprises [15]. So the importance of product quality can be related through an artificial intelligence system. The field of intelligent system has grown significantly and is believed to be capable of monitoring product quality in modern manufacturing system [16]. So quality managers looking for the best product fit take longer to make a decision because they spend more time searching for scattered product information [17]. Once quality managers begin to focus more on benefits and less on costs, the potential for making better quality decisions of intelligent system can be realized.

The decision making process discussed in this paper strives to develop an intelligent model that can be used to monitor and control the product quality of smart manufacturing system. This study is divided into the following subsections. Firstly, the modeling framework of intelligent decision making system is created based on FCM. Second, we will probe deeper into the modeling process of product quality control, and discuss relevant applications that have been found in the open literatures.

Finally, we will conclude this paper with a summary of the advances of product quality intelligent modeling that is expected to be realized based on FCM.

2. Description of Intelligent Modeling System

In fact, the implementation of high performance quality processing of manufacturing system is a challenging task. A lot of affective factors may also influenced decision making in intelligent system, because it touched on the human's subjectivity and experience. In the next section, intelligent modeling is identified in this paper based on FCM.

2.1 Modeling Framework of Intelligent Decision Making System

The main goal of the modeling framework is that decision efficiency is likely to improve when quality managers focus both on cost reduction and quality improvement. Then, the previous section was firstly used to introduce to the engineering applications customers, the FCM method and the various kinds of decision-making tools that are used to build the intelligent model. Several efforts have tried to overcome the limitations of the previous research approach by using intelligent decision making system.

On the other hand, the databases are created for data storage and model validation. The databases should have a sufficient size and include the maximum combination of inputs and outputs with types of information. In this approach, a series of raw data information is used as inputs into the database. Traditionally, intelligent manufacturing system employed for product quality decision making from other easily available data has used multivariate QC as inputs. The decision making process is based on fuzzy logic and reinforcement learning, which allows the intelligent system to deal with the uncertainty and ambiguity of the data input in different settings.

Moreover, the main objective of the intelligent system is the aggregation of individual judgments into a global value function. The ability to detect abrupt changes in manufacturing system is one of the most important functions in intelligent quality controlling [18]. However, the differences between traditional decision and intelligent decision making can be attributed to the technology that is available to the decision maker. Different types of modeling data input can be provided to the fuzzy inference engine for the decision making process. In this framework, the intelligent modeling system has been effectively developed.

It is easy to implement with few parameters in the process of construction of growth intelligent models. However, the complexity and difficulty of decision-making process can become cumbersome as the number of parameters grows. In this study, the modeling framework can be expressed with an analytical expression in Fig. 1.

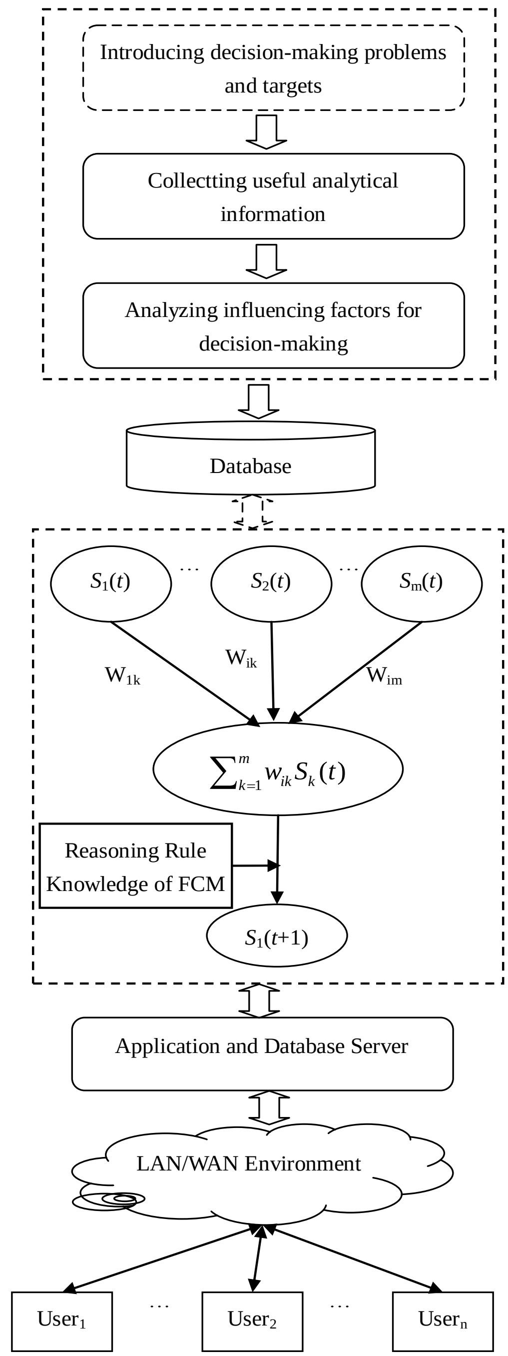

Fig. 1 Modeling framework of intelligent decision making system

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2.2 Intelligent Modeling Based on FCM

The goal of this approach is to aid the intelligent reasoning technology to improve the knowledge about the decision situation. We confirm that the FCM method for intelligent modeling is precise and applicable to decision making of manufacturing system. In recent years, FCM has become a hot spot of research [19]. The analytical expression of FCM has been successfully implemented in lots of manufacturing systems [20, 21]. In this paper, We applied our policies and methodologies in a real example based on FCM.

However, the prior researches have only solved the traditional decision making problems. In the traditional decision-making process, the criteria aggregation model is known a priori, while the total preference is unknown. The approaches that have been identified in the literature both involve the use of FCM and can be summarized as follows. FCM has been a preferred tool for intelligent modeling, and many researchers are now paying more and more attention to decision-making logic with it [22]. It has been shown by previous studies that FCM method is being successfully used in decision process [23]. This is due to the large scale regulations encompassed in reasoning process with FCM [24, 25].

Besides, FCM is usually designed to express the correlation and influence between different nodes by obtaining arrange of weights. Many such combinations of input and layer weights can be determined by the theory of fuzzy mathematics [26]. And the weights of FCM are generally scalars, but the causal knowledge can be implemented with a fuzzy number [27]. More detailed discussions about FCM are made the following arrangements [28].

The topological structure standard of FCM is described in the following:

$$U=(S,E,W) \tag{1}$$

Where, $S=\{S_1, S_2, \ldots\ldots, S_n\}$ denotes the Concept node of FCM; $E=\{<C_a, C_b>; C_a, C_b \in C\}$ denotes the causal relationship between nodes to arc; $W=\{W_{11}, W_{12}, \ldots\ldots, W_{nn}\}$ denotes the data correlation between nodes or influence. For instance, we can confirm the weight question with fuzzy numbers in the case of the global value function.

On the basis of above work, the uncertainty inference model based on FCM is constructed. The inference model and data structure of intelligent modeling system is discussed below. In this paper, the inference model of FCM method is described in Fig. 2.

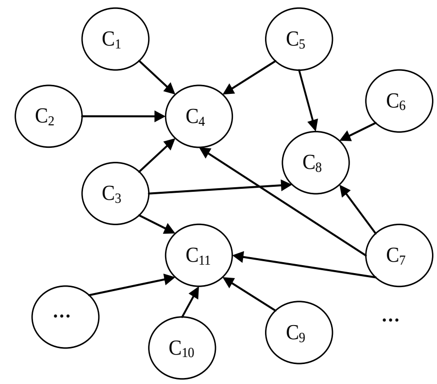

Fig. 2 The inference model of FCM

After all nodes were currently defined based on FCM theories and methods, the state matrix can be represented as shown below:

$$\alpha_U(t)=(S_1(t), S_2(t), \cdots, S_n(t)) \tag{2}$$

With the incidence matrix to express network topology, we can obtain the adjacency matrix from structure type synthesis in the following:

$$W_U(t)=\begin{bmatrix} w_{1,1} & w_{1,1} & \vdots & w_{1,m} \\ w_{2,1} & w_{2,2} & \vdots & w_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m,1} & w_{m,1} & \vdots & w_{m,m} \end{bmatrix} \tag{3}$$

In order to improve the veracity of modeling, a comprehensive evaluation method based on fuzzy synthesis judgment was presented in this paper. Based on fuzzy number definition and properties of principle, the decision of the manufacturing system was made available in the product quality control. This can take a value in [0, 1]. And the qualitative judgments of subject degree and weight are shown in Fig. 3.

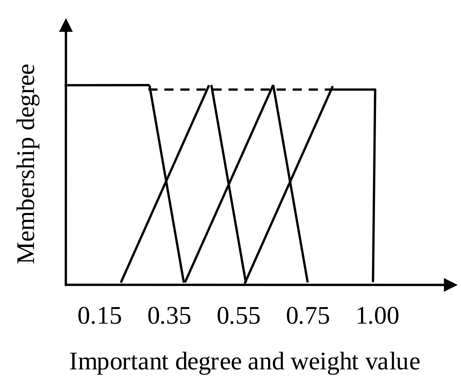

Fig. 3 The value of subject degree and weight

In order to reason the node in next state, we can apply the inference rules of FCM to make useful inferences about different message sequences in the following formula:

$$S_j(t+1) = f(\sum_{i=1}^{m} S_j(t) w_{ij}) = f(\begin{bmatrix} s_1(t) \\ s_1(t) \\ \vdots \\ s_m(t) \end{bmatrix} \begin{bmatrix} w_{1,1} & w_{1,1} & \vdots & w_{1,m} \\ w_{2,1} & w_{2,2} & \vdots & w_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m,1} & w_{m,1} & \vdots & w_{m,m} \end{bmatrix}) \quad (4)$$

In addition, FCM refers to a system modeling approach that is patterned after a comprehensive understanding of the fuzzy inference mechanism.

3. An Intelligent Decision Making System For Product Quality

The goal of this study is to implement an intelligent modeling system for product quality monitoring based on FCM method. So this paper presents the final results of a feasibility study on intelligent modeling for product quality monitoring in smart manufacturing system. Generally speaking, intelligent modeling capabilities have already been incorporated in a modern manufacturing system for experimental purposes. On the other hand, the hybrid algorithm developed has been applied on an original database consisting of quality control processes with multivariate QCs in the smart manufacturing system.

In order to describe the decision making of in quality control in a manufacturing system, we introduced the mechanism for managing the quality assurance process. Here, we analyze experimental results on the accuracy decision of FCM algorithm. The fuzzy cognitive map of multivariate QCs is shown in Fig. 4.

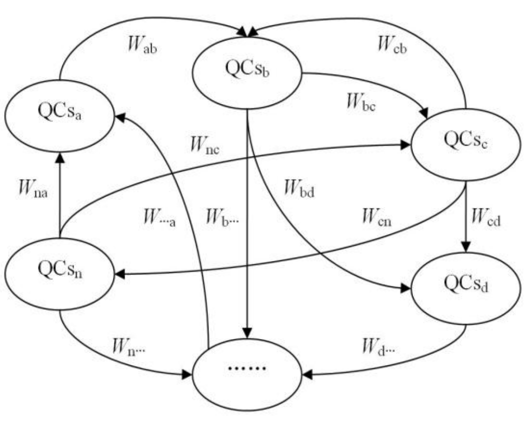

Fig. 4 The fuzzy cognitive map of multivariate QC

To assess the performance of the FCM algorithm, the cross-validation strategy has been used as a validation method. A brief description of intelligent modeling is given below for completeness in an example. The feasibility study, presented in this paper, is described below.

This paper mainly applies the means of decision analysis of product quality control in manufacturing system and chooses the case examples to carry on analyzing. Here is the example of standards and guidelines to consider. The manufacturing system consists of 8 QCs for product quality intelligent modeling process. These include quality awareness (QC_1), accuracy of the equipments (QC_2), stability of the equipments (QC_3), material strength (QC_4), material hardness (QC_5), system measurement (QC_6), environment characteristics (QC_7), feasibility of manufacturing methods (QC_8). Then, we can obtain the adjacency matrix from 8 QCs in the following:

$$W_8(t) = \begin{bmatrix} 0 & 0.15 & 0 & 0 & 0.50 & 0 & 0 & 0.75 \\ 0 & 0 & 0.65 & 0.25 & 0 & 0.20 & 0.25 & 0 \\ 0.35 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.80 & 0 & 0.15 & 0 & 0 & 0.80 \\ 0 & 0.40 & 0 & 0.35 & 0 & 0.65 & 0.35 & 1.00 \\ 0.60 & 0.25 & 0 & 0 & 0.15 & 0 & 0 & 0.20 \\ 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ 0.15 & 0 & 0 & 0 & 0.35 & 0 & 0.65 & 0 \end{bmatrix}$$

In this paper, we use vertex w to denote the concept and for its state. Given the binary concept value set used in the FCM, we can apply to represent the situation of different QC. Moreover the idea of credibility weights for decision makers is introduced. According to the FCM algorithm, the proposed linguistic weights are checked in terms of their neighborhood. The proposed method has the advantage that experts do not have to assign numerical causality weights for each indicator.

The first step in constructing the FCM model of product quality controlling is the determination of the concepts with FCM method. Many different decision makers following the algorithm developed the FCM model that is comprised of concepts group FCM. When the decision makers have described the concepts of the FCM model for monitoring the product quality in manufacturing system, the causal interconnections between different QCs have to be determined with our major manufacturing partners. A transformation process with the corresponding mechanism is needed to register each type of data source in manufacturing system. And the decision-making process of group FCM is described Fig. 5.

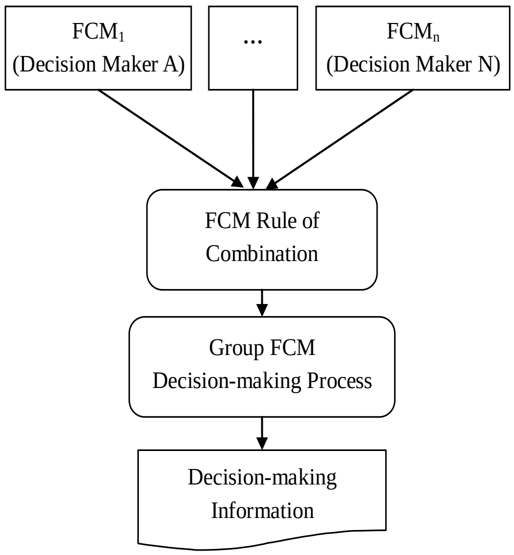

Fig. 5 The decision-making process of group FCM

FCM approach is an inference mechanism that allows the fuzzy causal relations among different factors. FCM models the decision making of a manufacturing system and offers a support to produce new knowledge based system applications. Here only a part of the intelligent decision making process has been developed to illustrate the role of the FCM model. Though the decision makers did not interact with each other during the modeling process, the degrees of influences from each expert's judgments individually can be obtained based on FCM model. In this paper, FCM can yield insights into indirect effects among all nodes under uncertain environment. The iterative process of FCM intelligent modeling is shown in Table 1.

Table 1: Iterative process of FCM intelligent modeling

	QC_1	QC_2	QC_3	QC_4	QC_5	QC_6	QC_7	QC_8
Iteration(1)	0.25	0.50	0.75	0.50	0.35	0.80	0.65	0.45
Iteration(2)	0.42	0.61	0.57	0.68	0.54	0.62	0.85	0.76
Iteration(3)	0.76	0.82	0.21	0.79	0.81	0.22	0.94	0.97
…	…	…	…	…	…	…	…	…
Hidden Pattern	0.95	0.97	0.07	0.93	0.98	0.05	0.97	1.00

It may be observed that the FCM was applied successfully in the study. From an engineering point of view, the decision making process can be thought a sort of statistics and artificial intelligence with database management. Extensive numerical experimentation is carried out in order to evaluate and validate different computational solutions for the implementation in decision making process. The level of such decisions for product quality is improving all the time. Besides, the statistical analysis assessing effectiveness of the intelligent system involved lots of comparison tests applied to the independent samples of computer runs.

4. Conclusions

In order to improve the usability of intelligent modeling for product quality decision making, a novel method has been proposed in this study based on FCM method. Different from a conventional product quality monitoring system, this approach aims to reduce the response time by processing the multivariate QC before they are transmitted to quality managers. Final results show good promise of the suitability of FCM approach for product quality intelligent modeling and decision making.
The intelligent system is implemented in product quality decision making process. It has been shown that the FCM could be used in intelligent modeling with effective results. The development of new decision making techniques based on intelligent modeling is necessary for increasing the correct ratio of quality control. Future research regarding intelligent modeling system with FCM aims to explore further the potentials in product quality decision making process.

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