Applications of Fuzzy Logic, Artificial Neural Network and Neuro-Fuzzy in Industrial Engineering

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Abstract. Artificial intelligence methods namely artificial neural network, fuzzy logic, and neuro-fuzzy have been effectively utilized in different applications like business, marketing, control engendering, health care, and social services. To demonstrate the usage of fuzzy set theory, artificial neural network, as well as neuro-fuzzy in industrial engineering and also for providing a basis for future investigation, a literature review of the artificial neural network, fuzzy logic, and neuro-fuzzy in industrial engineering is conducted in this paper.

Keywords: Fuzzy Logic, Artificial Neural Network, Neuro-Fuzzy, Industrial Engineering.

1 Introduction

Industrial engineering is one of the fields that artificial neural network, fuzzy logic, and neuro-fuzzy have found an extensive implementation area. Artificial neural networks can be considered as the most effective technique over the last few decades that are extensively utilized in a wide variety of implementations in different fields [1–6]. Artificial neural networks have been considered as efficient and versatile tools. They have learning ability as well as model-free characteristics.
Fuzzy systems are appropriate for estimated reasoning, mainly for the system with a mathematical design which is hard to obtain [7–11]. Fuzzy set theory can be considered as a major problem designing as well as a solution approach. The main contribution of

fuzzy logic is its ability to present vague data. Fuzzy logic has been implemented to design systems, which are difficult to define accurately. In recent years, successful implementations of fuzzy logic in industrial engineering have been reported. Industrial engineers encounter with numerous problems having incomplete as well as uncertain information [12–15]. Fuzzy logic theory can be considered as a capable tool for solving these kinds of problems. Fuzzy logic presents an effective tool to facilitate investigation in industrial engineering when the dynamics of the decision environment restrict the accurate evaluation of model parameters.

Neuro-fuzzy has been used in an extensive range of domains [16–18]. It is the combination of artificial neural networks and fuzzy logic. The cause of utilizing artificial neural networks with fuzzy logic is that artificial neural networks never make a presumption on the probability distribution functions of data [19]. Generally, the neuro-fuzzy model explains solutions better than artificial neural networks [20].

This paper represents details of the application of artificial neural network, fuzzy logic, and neuro-fuzzy in industrial engineering. In this paper, the most recent researches in the field of artificial neural network, fuzzy logic, and neuro- fuzzy are covered. Since some industries have successfully used these techniques, detailed discussions are supplied to stimulate future investigations. This article remaining sections are organized into four Sections. In Section 2 the applications of fuzzy logic in industrial engineering are given. In Section 3 the applications of artificial neural network in industrial engineering are given. Section 4 presents the applications of neuro-fuzzy in industrial engineering. Conclusions are included in Section 5.

2 Applications of fuzzy logic in industrial engineering

Fuzzy logic systems have been effectively applied in different industrial fields like automobile speed control [21], robot arm control [22], water quality control [23], and automatic train operation systems [24]. Fuzzy logic can be utilized for improving the efficiency of the system. Even though fuzzy logic is considered as an approach for presenting inaccurate and vague information, in [25] the Universal Approximation Theorem states that the fuzzy logic system can uniformly approximate any nonlinear function to any degree of preciseness.

The fuzzy inference system utilizes fuzzy set theory for mapping inputs to outputs. The common fuzzy inference system is Mamdani and Sugeno type. Fuzzy inference system consists of a fuzzification interface, a rule database, a decision making unit as well as defuzzification interface, see Fig. 1.

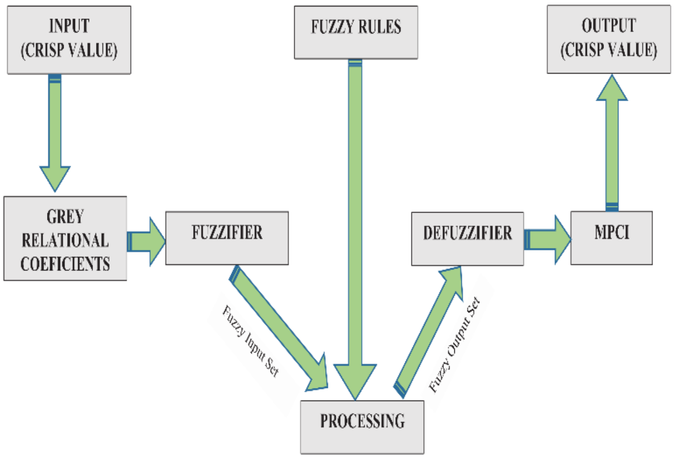

Fig. 1. The flowchart of a fuzzy inference system.

Fuzzy logic systems are extremely effective in highly complicated and nonlinear processes, and also in the lack of any simple mathematical model. In [26], fuzzy set theory is utilized for generating a novel pulse discriminator in electric dis- charge machining procedure. In electric discharge machining procedure, cutting efficiency indexes like material elimination rate as well as surface harshness are in direct relation with the electric discharge machining discharge pulses.

In [27], the fuzzy logic is utilized for control of the fluid catalytic cracking unit. In that paper, the fuzzy logic control as a control method is efficiently applied for improved procedure control of fluid catalytic cracking in the refinery process industry.

3 Applications of artificial neural network in industrial engineering

In contrast with the fuzzy system, the neural network is desirable at predicting. This potential originates from the learning ability as well as model-free characteristics. The design of the artificial neural network is based on a group of interconnected artificial neurons along with linear or nonlinear transfer functions. Neurons are placed in various layers such as input layer, hidden layer, as well as output layer. The artificial neural network learns the relevance between input and output of the system employing an iterative procedure named training. For every input into the neuron, there is a weight. Weight is a tune able number that is defined while training the network. A simple model of the artificial neural network is shown in Fig. 2.

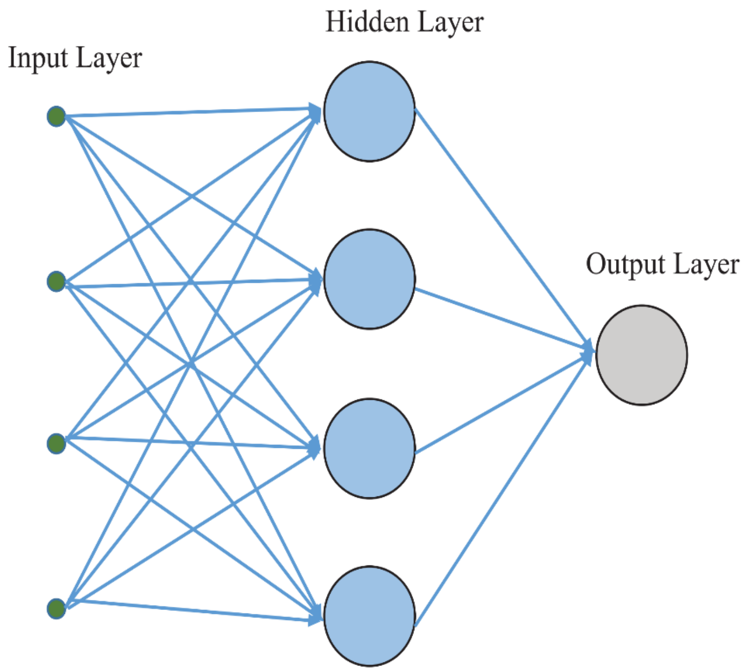

Fig. 2. A simple model of the artificial neural network.

One of the applications of the artificial neural network is in condition monitoring. Artificial neural network provides a reliable procedure to condition monitoring. Condition monitoring can be considered as an effective device in maintenance planning, also it can be utilized for avoiding the unpredicted failures. In [28], artificial neural network technique is used for experimentally recognizing gears as well as bearings faults related to a typical gearbox system.

The artificial neural network has been used for evaluating vibrations as well as recognizing fault existence. Fault detection is considered as a crucial issue for gas turbine owners to move from preventative repair to predictive repair and hence to decrease the repair expenses. In [29], artificial neural network technique is used for fault detection of an industrial gas turbine.

4 Applications of neuro-fuzzy in industrial engineering

Artificial neural network and fuzzy logic are both considered as model-free numerical techniques. Each technique uses an uncomplicated algorithmic procedure instead of a complex mathematical analysis, and also the parameters are tune- able [30]. These resemblances make it possible to combine the two techniques.

Neuro-fuzzy system is a multi-layer feedforward adaptive network which figures out the fundamental elements as well as functions of a standard fuzzy logic system. As

fuzzy logic systems are proved to be universal approximators, and since neuro-fuzzy systems are isomorphic to standard fuzzy logic systems concerning their functions hence neuro-fuzzy systems are likewise universal approximators [31]. For a special method in neuro-fuzzy, we can refer to the adaptive neuro-fuzzy inference system which is considered as one of the initial integrated hybrid neuro-fuzzy models [32].
One of the applications of the neuro-fuzzy system is in polymerization systems. Over the last few decades solubility of gases in polymers has been of interest to chemical engineers. In [33], a hybrid grid partitioning adaptive neuro-fuzzy inference system is utilized to predict carbon dioxide solubility in polymers.
The major aim of current manufacturing industries is to manufacture low cost, superb quality products in less time [34]. The choice of optimal cutting parameters is crucial in each machining procedure for increasing the quality of machined productions as well as to decrease the machining expenses. In [35], an adaptive neuro-fuzzy inference system is introduced to model and predict surface roughness in ball end milling of a die material. The algorithm developed in that paper presets the cutting parameters for a favorable level of surface roughness.

5 Conclusion

In this paper, the recent advances of the artificial neural network, fuzzy logic, and neuro-fuzzy applications in industrial engineering are provided. The artificial neural network, fuzzy logic, and neuro-fuzzy are the three major computational intelligence methods. Utilization of these models can be taken into account as a cheap, highly effective, and more reliable alternative devices. Therefore, these three methods can provide more ability to problem resolving than other techniques.

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