A Survey on Applications of Neuro-Fuzzy Models

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Abstract— **Artificial intelligence techniques such as neuro-fuzzy have been successfully applied in a wide variety of uses to be mentioned as economics, engineering, social science, and business. In order to show the implementations of neuro-fuzzy in engineering the most recent researches in the area of neuro-fuzzy are covered in this paper. As many researchers have effectively utilized neuro-fuzzy in engineering applications, detailed studies are provided in this work for stimulating future researches.**

Keywords-component; Artificial intelligence; neuro-fuzzy; engineering

I. INTRODUCTION

Fuzzy systems have been considered as an useful approach for approximated reasoning, generally for the system having a mathematical structure that is complex to acquire [1-5]. Fuzzy set theory is an appropriate approach to handle vagueness and has been successfully applied for solving multi-criteria decision making issues. In the past few years, important usages of fuzzy set theory in engineering have been provided [6-14]. Fuzzy set theory has been viewed as a proper technique to facilitate studies in engineering fields in a case that the dynamics of the decision domain bound the exact estimation of model parameters.

Through the years, investigators have developed the theory of fuzzy logic. Significant development is Z-numbers [15]. Z-numbers have been broadly utilized in numerous applications in various domains [16-18]. In [19] a new approach on the basis of Z-numbers is presented in order to handle the linguistic decision-making problems. In [20] an arithmetic approach to discrete Z-numbers is proposed. In [21] an arithmetic approach to continuous Z-numbers is proposed.

The combination of artificial neural networks and fuzzy logic have recently been employed in various fields. In [22-28] a diagnostic technique to optimize the energy performance as well as to maximize the operational time using artificial neural network and fuzzy logic is proposed. In [29] a neural as well as a fuzzy virtual flight recorder is built, which records aircraft control surface deviations. More recently, with the expansion of fuzzy logic, more researches have been carried out with the combination of artificial neural networks and Z-numbers. In [30] Bernstein neural network is used for finding the Z-number solutions of fuzzy differential equations. In [31], Z-number-based fuzzy system is suggested to determine the food security risk level.

This paper represents details of the application of neuro-fuzzy in industrial engineering. In this paper, the most recent researches in the field of neuro-fuzzy are covered. Since some industries have successfully used this technique, detailed discussions are supplied to stimulate future investigations. This article remaining sections are organized into three Sections. In Section 2 some basic definitions related to fuzzy numbers and Z-numbers are given. In Section 3 the applications of neuro-fuzzy in industrial engineering are given. Conclusions are included in Section 4.

II. MATHEMATICAL PRELIMINARIES

Here some necessary definitions of fuzzy numbers and Z-numbers are given.

Definition 1: If q is:

1) normal, there exists $\omega_0 \in \Re$ where $q(\omega_0) = 1$,

2) convex, $q(v\omega + (1-v)\omega) \geq \min\{q(\omega), q(\tau)\}$, $\forall \omega, \tau \in \Re, \forall v \in [0,1]$,

3) upper semi-continuous on $\Re, q(\omega) \leq q(\omega_0) + \epsilon$, $\forall \omega \in N(\omega_0)$, $\forall \omega_0 \in \Re, \forall \epsilon > 0, N(\omega_0)$ is a neighborhood,

4) $q^+ = \{\omega \in \Re, q(\omega) > 0\}$ is compact, so q is a fuzzy variable, $q \in E: \Re \to [0,1]$.

The fuzzy variable q is defined as below

$$q = (\underline{q}, \overline{q}) \tag{1}$$

such that $\underline{q}$ is the lower-bound variable and $\overline{q}$ is the upper-bound variable.

Definition 2: The Z -number is composed of two elements . $q(\omega)$ is considered as the restriction on the real-valued uncertain variable ω and p is considered as a measure of the reliability of q . The Z -number is defined as Z^+ -number, when $q(\omega)$ is a fuzzy number and p is the probability distribution of . If (ω) , and p , are fuzzy numbers, then the Z -number is defined as Z^- -number.

The Z^+ -number has more information in comparison with the Z^- -number. In this work, we use the definition of Z^+ -number, i.e., $Z = [q, p]$, q is a fuzzy number and p is a probability distribution.

The triangular membership function is defined as

$$\mu_q = G(a, b, c) = \begin{cases} \frac{\omega - a}{b - a} & a \leq \omega \leq b \\ \frac{c - \omega}{c - b} & b \leq \omega \leq c \end{cases} \quad otherwise\, \mu_q = 0 \tag{2}$$

and the trapezoidal membership function is defined as

$$\mu_q = G(a, b, c, d) = \begin{cases} \frac{\omega - a}{b - a} & a \leq \omega \leq b \\ \frac{d - \omega}{d - c} & c \leq \omega \leq d \\ 1 & b \leq \omega \leq c \end{cases} \quad otherwise\, \mu_q = 0 \tag{3}$$

The probability measure of q is defined as

$$p(q) = \int_{\mathbb{R}} \mu_q(\omega) p(\omega) d\omega \tag{4}$$

such that p is the probability density of ω . For discrete $Z-$ -numbers we have

$$p(q) = \sum_{j=1}^{n} \mu_q(\omega_j) p(\omega_j) \tag{5}$$

Definition 3: The α -level of the Z –number $Z = (q, p)$ is stated as below

$$[Z]^\alpha = ([q]^\alpha, [p]^\alpha) \tag{6}$$

$$0 < \alpha <$$

such that . $[p]^\alpha$ is calculated by the Nguyen's theorem

$$[p]^\alpha = p([q]^\alpha) = p\left(\left[\underline{q}^\alpha, \overline{q}^\alpha\right]\right) = \left[\underline{P}^\alpha, \overline{P}^\alpha\right] \tag{7}$$

such that $p([q]^\alpha) = \{p(\omega) | \omega \in [q]^\alpha\}$. Hence, $[Z]^\alpha$ is defined as

$$[Z]^\alpha = \left(\underline{Z}^\alpha, \overline{Z}^\alpha\right) = \left(\left(\underline{q}^\alpha, \underline{P}^\alpha\right), \left(\overline{q}^\alpha, \overline{P}^\alpha\right)\right) \tag{8}$$

such that $\underline{P}^\alpha = \underline{q}^\alpha p\left(\underline{\omega}_j^\alpha\right)$, $\overline{P}^\alpha = \overline{q}^\alpha p(\overline{\omega}_j^\alpha)$, $[\omega_j]^\alpha = \left(\underline{\omega}_j^\alpha, \overline{\omega}_j^\alpha\right)$.

Let $Z_1 = (q_1, p_1)$ and $Z_2 = (q_2, p_2)$, we have

$$Z_{12} = Z_1 * Z_2 = (q_1 * q_2, p_1 * p_2) \tag{9}$$

where $* \in \{\oplus, \ominus, \odot\}$. $\oplus$, $\ominus$ and $\odot$, indicate sum, subtract and multiply respectively.

The operations utilized for the fuzzy numbers $[q_1]^\alpha = [q_{11}^\alpha, q_{12}^\alpha]$ and are defined as [32],

$$[q_1 \oplus q_2]^\alpha = [q_1]^\alpha + [q_2]^\alpha = [q_{11}^\alpha + q_{21}^\alpha, q_{12}^\alpha + q_{22}^\alpha]$$

$$[q_1 \ominus q_2]^\alpha = [q_1]^\alpha - [q_2]^\alpha = [q_{11}^\alpha - q_{21}^\alpha, q_{12}^\alpha - q_{22}^\alpha] \tag{10}$$

$$[q_1 \odot q_2]^\alpha = \begin{pmatrix} \min\{q_{11}^\alpha q_{21}^\alpha, q_{11}^\alpha q_{22}^\alpha, q_{12}^\alpha q_{21}^\alpha, q_{12}^\alpha q_{22}^\alpha\} \\ \max\{q_{11}^\alpha q_{21}^\alpha, q_{11}^\alpha q_{22}^\alpha, q_{12}^\alpha q_{21}^\alpha, q_{12}^\alpha q_{22}^\alpha\} \end{pmatrix}$$

For the discrete probability distributions, the following relation is defined for all $p_1 * p_2$ operations

$$p_1 * p_2 = \sum_l p_1(\omega_{1,j}) p_2\left(\omega_{2,(n-j)}\right) = p_{12}(\omega) \tag{11}$$

III. APPLICATIONS OF NEURO-FUZZY IN INDUSTRIAL ENGINEERING

A. Background and related work

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 tuneable [33]. These resemblances make it possible to combine the two techniques.

Neuro-fuzzy system has been widely utilized in polymerization systems. In [34], an adaptive neuro-fuzzy inference system is applied for predicting carbon dioxide solubility in polymers.

In [35], an adaptive neuro-fuzzy inference system is proposed for modeling the surface roughness in ball end milling of a die material. The approach suggested in that paper adjusts the cutting parameters for a derivable rate of surface harshness.

In [36] neural network technique is used to obtain the approximate solutions of the fuzzy equations with Z-number coefficients. The solutions of fuzzy equations are the controllers when the desired references are considered as the outputs.

In [30] the solutions of fuzzy differential equations are estimated using Bernstein neural networks where the uncertainties are in the form of Z- numbers. At first the fuzzy

differential equation is converted into four ordinary differential equations with Hukuhara differentiability. Afterward, neural models are developed using the structure of ordinary differential equations.

B. Neural networks

Neural networks are constructed from neurons and synapses [37-40]. They alter their rates in reply from nearby neurons as well as synapses. Neural networks operate similar to computer as they map inputs to outputs. Neurons, as well as synapses, are silicon members, which mimic their treatment. A neuron gathers the total incoming signals from other neurons, afterward simulate its reply represented by a number. Signals move among the synapses, which contain numerical rates. Neural networks learn once they vary the value of their synapsis. A common neural network with synaptic connections is presented in Figure 1.
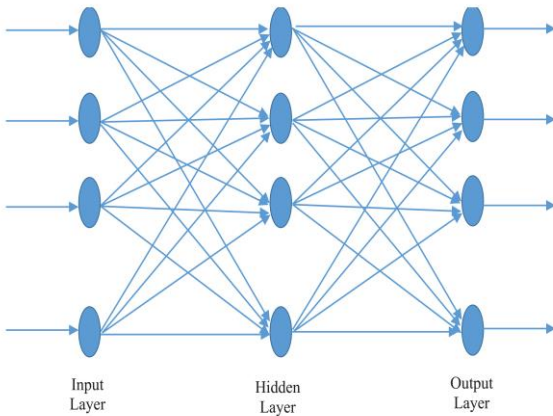

Figure 1.   A common neural network

C. Fuzzy expert system

The fuzzy expert system applies fuzzy logic in lieu of Boolean logic. It is the most general utilization of fuzzy logic. It is utilized in various areas such as:

- Linear and nonlinear control
- Pattern recognition
- Financial systems

The fuzzy inference systems for industrial position factor analysis is partitioned into three major parts: the fuzzifier, the knowledge management and the defuzzifier (Figure 2). The fuzzifier and the defuzzifier transform exterior information in fuzzy values and conversely. The knowledge management applies the fuzzy rules related to the knowledge basis which permits for estimate logic [41].
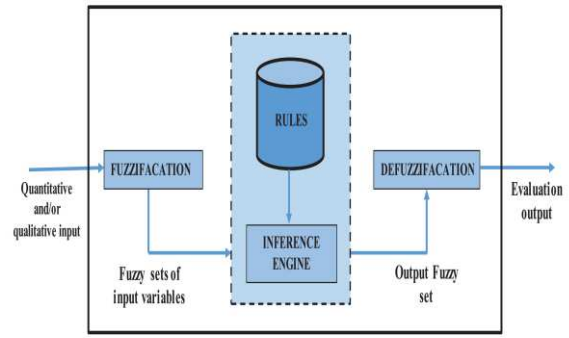

Figure 2.   Fuzzy expert system

D. Fuzzy If-Then rules

Fuzzy logic usually applies If-Then rules. A single fuzzy If-Then rule is stated as follows:

such that x_1 and y_2 are taken to be the linguistic variables stated by fuzzy sets on the domains P and Q, respectively. The If sector of the rule " is x_1 " is named as the antecedent and the Then sector of the rule " q is y_2 " is named as the consequent.

Furthermore, the conditional statement is defined as follows:

$$\text{If } x_1 \text{ Then } y_2 \text{ or } x_1 \rightarrow y_2$$

Example 1 Speed as well as pressure of a steam engine is defined with the below linguistic expression

If speed is slow then pressure is high

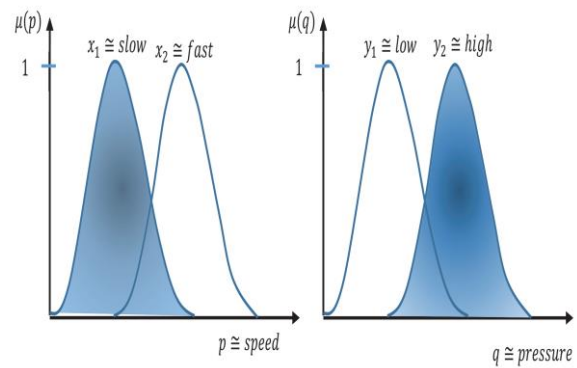The statement is demonstrated in Figure 3.

Figure 3.   Fuzzy If-Then rule

E. Advantageous and drawbacks of fuzzy based systems

Fuzzy based systems have the following advantageous:

I.   Excellent accuracy on results.

II.   Same as human logic.

III. Utilizations of easy mathematical models to solve real world problems linear or non-linear.

IV. Utilized for fast operations as well as decision control.

V. Extremely effective for rule based modeling as well as membership evaluations.

Fuzzy based systems have the following drawbacks:

I. Poor speed and lengthy running time needed.

II. Absence of real-time answer.

III. For accurate outcomes require to involve an important quantity of data, which furthermore rises rules for reasoning.

F. Why apply Z-numbers in neural networks

Each neuron in the artificial neural network is linked with another neuron via a connection link in such a manner that the connecting link is related to a weight with the information regarding the input signal. Therefore, the weights contain beneficial information regarding input to resolve the problems. Some reasons for applying Z-numbers in neural networks are as follows:

I. In a case that crisp values cannot be implemented, uncertain values such as Z-numbers are utilized.

II. Since the training, as well as learning, assist neural network to have a high performance in unanticipated status, therefore in such status, uncertain values like Z-numbers are more suitable than crisp values.

III. In neural networks, Z-numbers are more applicable than fuzzy numbers. Z-numbers are more precise when compared with fuzzy numbers. Also, Z-numbers have less difficulty in computation in comparison with nonlinear system modeling approaches.

G. Complexity in applying Z-numbers in neural networks

There exist some troubles when utilizing Z-numbers in neural networks. The complexity is associated with membership rules, the requirement to construct an uncertain system since it is often difficult to derive it by supplied set of complicated data.

Neural networks can be used to train Z-numbers. The advantageous of using neural networks for training Z-numbers are as follows:

I. Novel patterns of data may be learned simply using neural networks therefore, it may be utilized for preprocessing data in uncertain systems.

II. Neural networks due to their abilities in learning new relation with new input data may be utilized for refining fuzzy rules to generate the fuzzy adaptive system.

Example 2 The photo voltaic cells (PV cells) have been used for generating electricity from sun which are modeled in a parallel form, see Figure 4. Based on the variations in the location of sun and status of climate, the radiation of sun alters and consequently the current as well as voltage generated by

PV cells change. The power generation using PV cells can be modeled as below [42],

$$J = a_1 p_1 q_1 \oplus a_2 p_2 q_2 \oplus a_3 p_3 q_3 \oplus a_4 p_4 q_4 \quad (12)$$

such that $p_1 = \rho, p_2 = \sqrt{\rho}, p_3 = \dfrac{\rho}{4}, p_4 = \rho^3$ are the currents also $q_1 = 2\varphi, q_2 = \sqrt{3\varphi}, q_3 = \dfrac{\varphi}{2}, q_4 = \varphi^4$ are the voltages generated by PV cells, also ρ and φ are taken to be the elapsed time. The characteristic coefficients of the PV cell are

$$a_1 = [(3,6,\mathbf{8}), p(0.7, 0.83, 0.9)]$$
$$a_2 = [(2,5,\mathbf{9}), p(0.8, 0.9, 1)]$$
$$a_3 = [(4,5,\mathbf{9}), p(0.7, 0.87, 0.9)]$$
$$a_4 = [(7,10,12), p(0.8, 0.85, 0.92)]$$
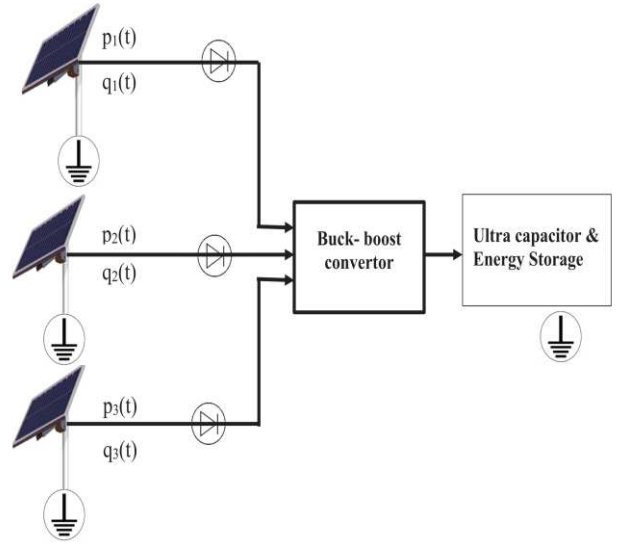$$(13)$$

Figure 4. PV cells

The following inputs have been used for training the neural network in order to obtain the characteristic coefficients of the PV cells (12)

$$\rho = \begin{cases} [(2,6,\mathbf{7}), p(0.8, 0.85, 0.92)], \\ [(11,14,19), p(0.7, 0.86, 0.9)], \\ [(9,11,13), p(0.8, 0.9, 1)], \\ [(1,2,3), p(0.7, 0.83, 0.9)] \end{cases} \quad (14)$$

$$\varphi = \begin{cases} [(1,2,\mathbf{5}), p(0.7, 0.82, 0.9)] \\ [(10,12,14), p(0.85, 0.9, 1)] \\ [(9,11,15), p(0.71, 0.87, 0.9)] \\ [(3,6,\mathbf{7}), p(0.8, 0.85, 0.91)] \end{cases} \quad (15)$$

The outputs data related to (12) are

$$J = \begin{cases} [(723.32, 752.91, 791.23), p(0.7, 0.86, \mathbf{0.9})], \\ [(5123.63, 7564.17, 9233.22), p(0.8, 0.9, 1)], \\ [(3121.63, 3789.92, 4462.31), p(0.85, 0.9, 1)], \\ [(753.82, 811.44, 883.94), p(0.71, 0.87, 0.9)] \end{cases} \quad (16)$$
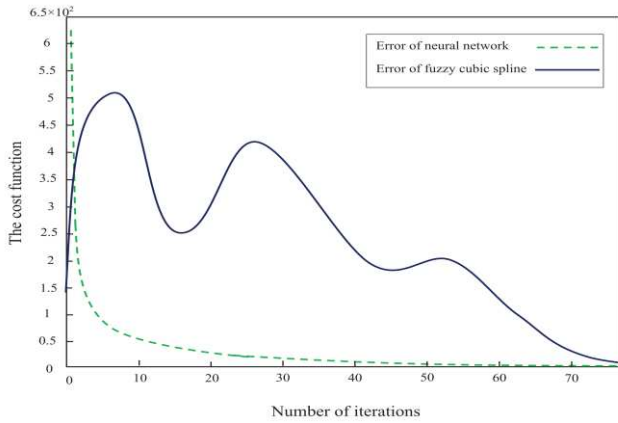
Figure 5.   Approximated errors

Figure 5 demonstrates the precision of the neural network technique in obtaining the Z-number coefficients of (12). In this figure, the fuzzy cubic spline technique has been used for comparison.

Example 3 Consider the following equation

$$\begin{cases} (6,8,10) \odot V \odot I \oplus (4,7,9) \odot V^2 \odot I^2 \\ \qquad = (52.1453,7123) \\ (8,11,13) \odot V \odot I \oplus (5,7,10) \odot V^2 \odot I^2 \\ \qquad = (74.2134,9651) \end{cases} \quad (17)$$

where $V = (-6,-4,-1)$ and $(-7,-6,-3)$ are the exact solutions. Neural network technique can be used for obtaining the approximate solutions of (12). The error between the approximate solutions and the exact solutions is demonstrated in Figure 6.
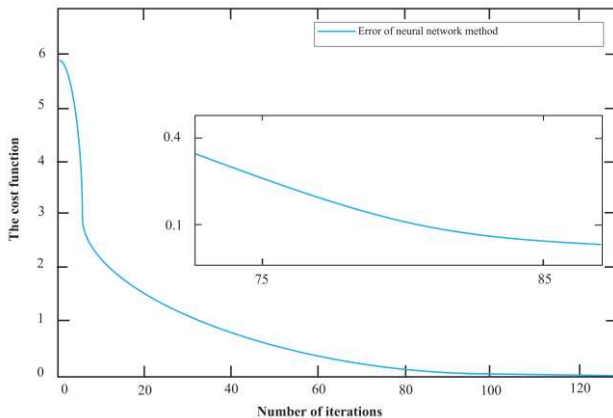

Figure 6.   The error between the approximate solution and the exact solution

IV.   CONCLUSION

Engineers are always dealing with many different kinds of measures as well as evaluations. Nevertheless, all the measurement of information may not be represented as an explicit number. In this work, the current applications of the neuro-fuzzy in industrial engineering are given. The neuro-fuzzy is one of the major computational intelligence approaches. Implementation of this technique may be considered as an inexpensive, highly potent, as well as more reliable alternative tool. Hence, this approach provides high capability to problem solving when compared with other approaches.

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