22

Neural Network and Adaptive Neuro-Fuzzy Inference System Applied to Civil Engineering Problems

Mohammed A. Mashrei
Thi-Qar University, College of Engineering, Civil Department
Iraq

1. Introduction

Soft computing is an approximate solution to a precisely formulated problem or more typically, an approximate solution to an imprecisely formulated problem (Zadeh, 1993). It is a new field appearing in the recent past to solve some problems such as decision-making, modeling and control problems. Soft computing is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision (Jang el at., 1997). It consists of many complementary tools such as artificial neural network (ANN), fuzzy logic (FL), and adaptive neuro-fuzzy inference system (ANFIS).

Artificial neural network (ANN) model is a system of interconnected computational neurons arranged in an organized fashion to carry out an extensive computing to perform a mathematical mapping (Rafiq et al., 2001). The first interest in neural network (or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch & Pitts, (1943). These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational works. ANN can be most adequately characterized as a computational model with particular properties such as the ability to adapt or learn, to generalize, or to cluster or organize data in which the operation is based on parallel processing.

ANN has a large number of highly interconnected processing elements (nodes or units) that usually operate in parallel and are configured in regular architectures. The collective behavior of an ANN, like a human brain, demonstrates the ability to learn, recall, and generalize from training patterns or data. ANN is inspired by modeling networks of biological neurons in the brain. Hence, the processing elements in ANN are also called artificial neurons (Rafiq et al., 2001). Artificial neural network described in this chapter is mostly applied to solve many civil engineering applications such as structural analysis and design (Cladera & Mar, 2004a, 2004b; Hajela & Berke, 1991; Sanad & Saka, 2001), structural damage assessment (Feng & Bahng, 1999; Mukherjee et al., 1996), structural dynamics and control (Chen et al., 1995; Feng & Kim, 1998) and pavement condition-rating modeling (Eldin & Senouuci, 1995).

The adaptive neuro-fuzzy inference system (ANFIS), first proposed by Jang, 1993, is one of the examples of neuro-fuzzy systems in which a fuzzy system is implemented in the framework of adaptive networks. ANFIS constructs an input-output mapping based both on human knowledge (in the form of fuzzy if-then rules) and on generated input-output data pairs by using a hybrid algorithm that is the combination of the gradient descent and least squares estimates. Readers are referred to References (Jang, 1993; Mashrei, 2010) for more details on the ANFIS. After generated input-output by training, the ANFIS can be used to recognize data that is similar to any of the examples shown during the training phase .The adaptive neuro-fuzzy inference system has been used in the area of civil engineering to solve many problems (Abdulkadir et al., 2006; Akbulut et al., 2004; Fonseca el at., 2007; Tesfamariam & Najjaran, 2007).

Most of the problems solved in civil and structural engineering using ANFIS and ANN are prediction of behavior based on given experimental results that are used for training and testing data. The matter of modeling is to solve a problem by predicting which is obtained by mapping a set of variables in input space to a set of response variables in output space through a model as represented in Fig. 1. In the box representing a model in this figure, conventionally a mathematical model is used. However, the conventional modeling of the underlying systems often tends to become quite intractable and very difficult. Recently an alternative approach to modeling has emerged under the rubric of soft computing with neural network and fuzzy logic as its main constituents. The development of these models, however, requires a set of data. Fortunately, for many problems of civil engineering such data are available.

The purpose of this chapter is to investigate the accuracy of an adaptive neuro-fuzzy inference system and neural network to solve civil engineering problems: The ANN and ANFIS are used to predict the shear strength of concrete beams reinforced with fiber reinforced polymer (FRP) bars and shear strength of ferrocement members. The performance of the ANFIS and ANN models are compared with experimental values and with those of the other methods to assess the efficiency of these models. The study is based on the available databases.

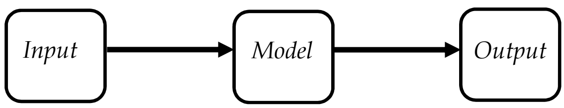


Fig. 1. An input-output mapping

2. Artificial neural network

One type of network sees the nodes as artificial neurons. These are called artificial neural network (ANN). An artificial neuron is a computational model inspired in by natural neurons. Natural neurons receive signals through *synapses* located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain *threshold*), the neuron is *activated* and emits a signal through the *axon*. This signal might be sent to another synapse, and might activate other neurons (Gershenson, 2003). Fig. 2 shows a natural neuron.

The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of *inputs*(like synapses), which are multiplied by *weights* (strength of the respective signals), and then computed by a mathematical function which determines the *activation* of the neuron. Another function (which may be the identity) computes the *output* of the artificial neuron (sometimes independent on a certain *threshold*). ANN combines artificial neurons in order to process information (Gershenson, 2003).

Compared to conventional digital computing techniques, neural networks are advantageous because of their special features, such as the massively parallel processing, distributed storing of information, low sensitivity to error, their very robust operation after training, generalization and adaptability to new information (Waszczyszyn, 1998).

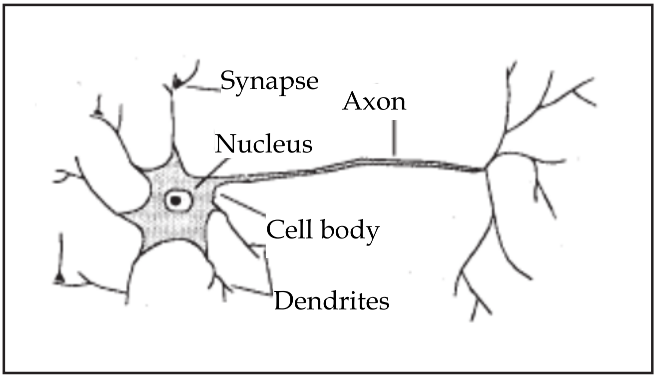


Fig. 2. Natural (biological) neurons

2.1 Learning process

An artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs. Inputs are information that enters the cell from other cells of from external world. Weights are values that express the effect of an input set or another process element in the previous layer on this process element. Sum function is a function that calculates the effect of inputs and weights totally on this process element. This function calculates the net input that comes to a cell (Topcu & Sarıdemir, 2007).

The information is propagated through the neural network layer by layer, always in the same direction. Besides the input and output layers there can be other intermediate layers of neurons, which are usually called hidden layers. Fig. 3 shows the structure of a typical neural network.

The inputs to the j^{th} node are represented as an input factor, a, with component a_i (i=1 to n), and the output by bj. The values w_{1j}, w_{2j}, …, and w_{nj} are weight factors associated with each input to the node. This is something like the varying synaptic strengths of biological neurons. Weights are adaptive coefficients within the network that determine the intensity of the input signal. Every input (a_1, a_2, …, a_n) is multiplied by its corresponding weight factor (w_{1j}, w_{2j}, …, w_{nj}), and the node uses this weighted input (w_{1j} a_1, w_{2j} a_2, …, w_{nj} a_n) to perform further calculations. If the weight factor is positive, ($w_{ij}a_i$) tends to excite the node. If the weight factor is negative, ($w_{ij}a_i$) inhibits the node. In the initial setup of a neural network, weight factors may be chosen according to a specified statistical distribution. Then these weight factors are adjusted in the development of the network or "learning" process.

The other input to the node is the node's internal threshold, T_j. This is a randomly chosen value that governs the "activation" or total input of the node through the following equation (Baughman & Liu, 1995).

Total Activation: $$x_i = \sum_{i=1}^{n}(w_{ij}).a_i - T_j \quad (1)$$

The total activation depends on the magnitude of the internal threshold T_j. If T_j is large or positive, the node has a high internal threshold, thus inhibiting node-firing. If T_j is zero or negative, the node has a low internal threshold, which excites node-firing. If no internal threshold is specified, a zero value is assumed. This activity is then modified by transfer function and becomes the final output (b_j) of the neuron (Baughman & Liu, 1995).

$$b_j = f(x_i) = f\left(\sum_{i=1}^{n}(w_{ij}).a_i - T_j\right) \quad (2)$$

This signal is then propagated to the neurons (process elements) of the next layer. Fig. 4 depicts this process.

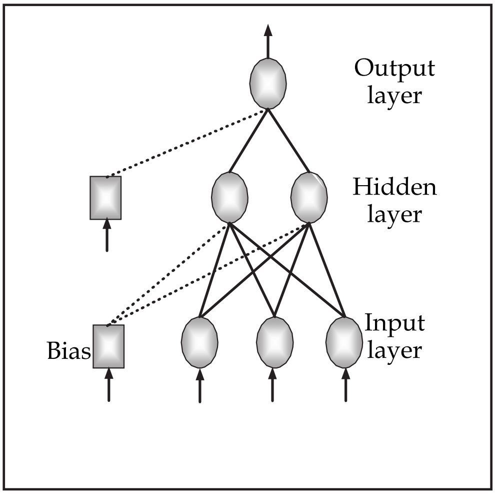


Fig. 3. Structure of a typical neural network

A back-propagation neural network has been successfully applied in various fields such as in civil engineering problems. A learning with back-propagation technique starts with applying an input vector to the network, which is propagated in a forward propagation mode which ends with an output vector. Next, the network evaluates the errors between the desired output vector and the actual output vector. It uses these errors to shift the connection weights and biases according to a learning rule that tends to minimize the error. This process is generally referred to as "error back- propagation" or back-propagation. The adjusted weights and biases are then used to start a new cycle. A back-propagation cycle, also known as an epoch, in a neural network is illustrated in Fig. 5. For a number of epochs the weights and biases are shifted until the deviations from the outputs are minimized.

Transfer functions are the processing units of a neuron. The node's output is determined by using a mathematical operation on the total activation of the node. These functions can be linear or non-linear. Three of the most common transfer functions are depicted in Fig. 6.

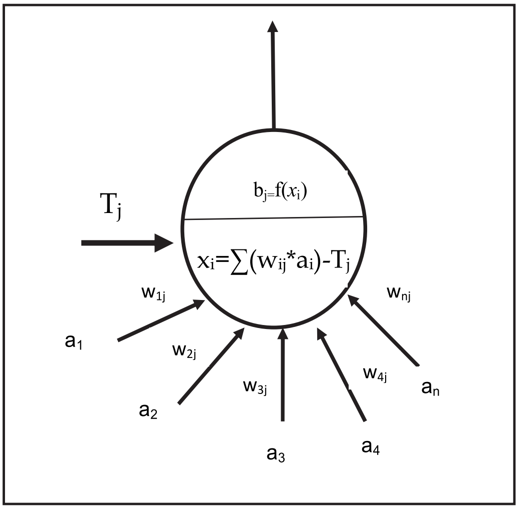


Fig. 4. A single neuron

The mathematical formulation of the functions is given as follows (Matlab Toolbox, 2009):

Pure-Linear: $f(x) = x$ (3)

Log sigmoid: $f(x) = 1/1 + e^{-x}$ $\quad 0 \le f(x) \le 1$ (4)

Tangent sigmoid: $f(x) = \tanh(x) = e^{x} - e^{-x}/e^{x} + e^{-x}$ $\quad -1 \le f(x) \le 1$ (5)

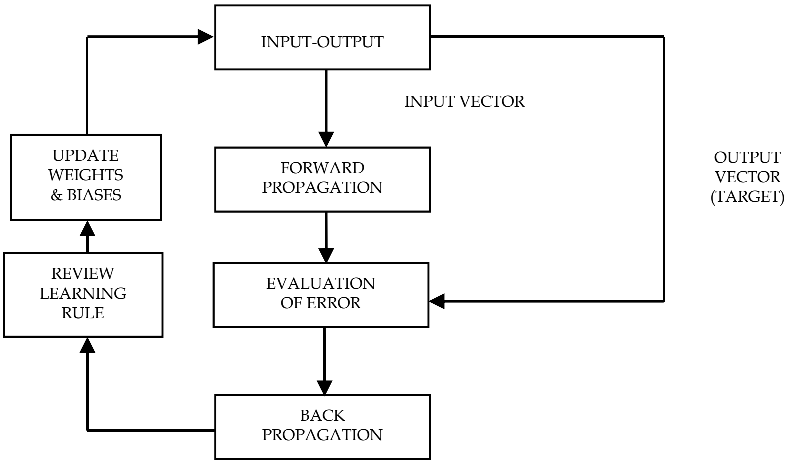


Fig. 5. Back-propagation cycle

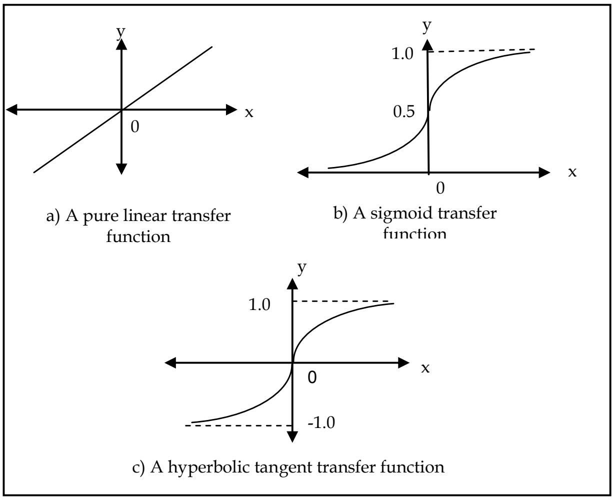


Fig. 6. Commonly used transfer function

2.2 Generalization

After the training is completed, the network error is usually minimized and the network output shows reasonable similarities with the target output, and before a neural network can be used with any degree of confidence, there is a need to establish the validity of the results it generates. A network could provide almost perfect answers to the set of problems with which it was trained, but fail to produce meaningful answers to other examples. Usually, validation involves evaluating network performance on a set of test problem that were not used for training. Generalization (testing) is so named because it measures how well the network can generalize what it has learned and form rules with which to make decisions about data it has not previously seen. The error between the actual and predicted outputs of testing and training converges upon the same point corresponding to the best set of weight factors for the network. If the network is learning an accurate generalized solution to the problem, the average error curve for the test patterns decreases at a rate approaching that of the training patterns. Generalization capability can be used to evaluate the behavior of the neural network.

2.3 Selecting the number of hidden layers

The number of hidden layers and the number of nodes in one hidden layer are not straightforward to ascertain. No rules are available to determine the exact number. The choice of the number of hidden layers and the nodes in the hidden layer(s) depends on the network application. Determining the number of hidden layers is a critical part of designing a network and it is not straightforward as it is for input and output layers (Rafiq el at., 2001).

To determine the optimal number of hidden layers, and the optimal number of nodes in each layer, the network is to be trained using various configurations, and then to select the configuration with the fewest number of layers and nodes that still yields the minimum mean-squares error (MSE) quickly and efficiently. (Eberhard & Dobbins, 1990) recommended the number of hidden-layer nodes be at least greater than the square root of the sum of the number of the components in the input and output vectors. (Carpenter & Barthelemy, 1994; Hajela & Berke, 1991) suggested that the number of nodes in the hidden layer is between the sum and the average of the number of nodes in the input and output layers.

The number of nodes in the hidden layer will be selected according to the following rules:

1. The maximum error of the output network parameters should be as small as possible for both training patterns and testing patterns.
2. The training epochs (number of iteration) should be as few as possible.

2.4 Pre-process and post-process of the training patterns

Neural networks require that their input and output data are normalized to have the same order of magnitude. Normalization is very critical; if the input and the output variables are not of the same order of magnitude, some variables may appear to have more significance than they actually do. The normalization used in the training algorithm compensates for the order-of-differences in magnitude of variables by adjusting the network weights. To avoid such problems, normalization all input and output variables is recommended. The training patterns should be normalized before they are applied to the neural network so as to limit the input and output values within a specified range. This is due to the large difference in the values of the data provided to the neural network. Besides, the activation function used in the back-propagation neural network is a sigmoid function or hyperbolic tangent function. The lower and upper limits of the function are 0 and 1, respectively for sigmoid function and are -1 and +1 for hyperbolic tangent function. The following formula is used to pre-process the input data sets whose values are between -1 and 1(Baughman & Liu, 1995).

$$x_{i,norm.} = 2.\frac{x_i - x_{i,\min.}}{x_{i,\max.} - x_{i,\min.}} - 1 \tag{6}$$

where:
$x_{i,norm}$: the normalized variable.
$x_{i,min}$: the minimum value of variable xi (input).
$x_{i,max}$: the maximum value of variable xi (input).

However, for the sigmoid function the following function might be used.

$$O_{i,norm} = \frac{t_i - t_{i,min}}{t_{i,max} - t_{i,min}} \tag{7}$$

where:
$t_{i,min}$: the minimum value of variable t_i (output).
$t_{i,max}$: the maximum value of variable t_i (output).

3. Adaptive neuro-fuzzy inference system (ANFIS)

The fuzzy set theory developed by (Zadeh, 1965) provides as a mathematical framework to deal with vagueness associated with the description of a variable. The commonly used fuzzy inference system (FIS) is the actual process of mapping from a given input to output using fuzzy logic.

Fuzzy logic is particularly useful in the development of expert systems. Expert systems are built by capturing the knowledge of humans: however, such knowledge is known to be qualitative and inexact. Experts may be only partially knowledgeable about the problem domain, or data may not be fully available, but decisions are still expected. In these situations, educated guesses need to be made to provide solutions to problems. This is where fuzzy logic can be employed as a tool to deal with imprecision and qualitative aspects that are associated with problem solving (Jang, 1993).

A fuzzy set is a set without clear or sharp boundaries or without binary membership characteristics. Unlike a conventional set where object either belongs or do not belong to the set, partial membership in a fuzzy set is possible. In other words, there is a softness associated with the membership of elements in a fuzzy set (Jang, 1993).A fuzzy set may be represented by a membership function. This function gives the grade (degree) of membership within the set. The membership function maps the elements of the universe on to numerical values in the interval [0, 1]. The membership functions most commonly used in control theory are triangular, trapezoidal, Gaussian, generalized bell, sigmoidal and difference sigmoidal membership functions (Jang et al., 1997; Matlab toolbox, 2009; Zaho & Bose, 2002).

As mentioned previously, the fuzzy inference system is the process of formulating the mapping from a given input to an output using fuzzy logic. The dynamic behavior of an FIS is characterized by a set of linguistic description rules based on expert knowledge.

The fuzzy system and neural networks are complementary technologies.The most important reason for combining fuzzy systems with neural networks is to use the learning capability of neural network. While the learning capability is an advantage from the view point of a fuzzy system, from the viewpoint of a neural network there are additional advantages to a combined system. Because a neuro-fuzzy system is based on linguistic rules, we can easily integrate prior knowledge in to the system, and this can substantially shorten the learning process. One of the popular integrated systems is an ANFIS, which is an integration of a fuzzy inference system with a back-propagation algorithm (Jang et al., 1997; Lin & Lee 1996).

There are two types of fuzzy inference systems that can be implemented: Mamdani-type and Sugeno-type (Mamdani & Assilian, 1975; Sugeno, 1985). Because the Sugeno system is more compact and computationally more efficient than a Mamdani system, it lends itself to the use of adaptive techniques for constructing the fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system best models the data. The fuzzy inference system based on neuro-adaptive learning techniques is termed adaptive neuro-fuzzy inference system (Hamidian & Seyedpoor, 2009).

In order for an FIS to be mature and well established so that it can work appropriately in prediction mode, its initial structure and parameters (linear and non-linear) need to be tuned or adapted through a learning process using a sufficient input-output pattern of data. One of the most commonly used learning systems for adapting the linear and non-linear parameters of an FIS, particularly the first order Sugeno fuzzy model, is the ANFIS. ANFIS is a class of adaptive networks that are functionally equivalent to fuzzy inference systems (Jang, 1993).

3.1 Architecture of ANFIS

Fig. 7 shows the architecture of a typical ANFIS with two inputs X_1 and X_2, two rules and one output *f*, for the first order Sugeno fuzzy model, where each input is assumed to have two associated membership functions (MFs). For a first-order Sugeno fuzzy model a typical rule set with two fuzzy if–then rules can be expressed as (Jang, 1993):

Rule (1): If X_1 is A_1 and X_2 is B_1, then $f_1 = m_1 X_1 + n_1 X_2 + q_1$,
Rule (2): If X_1 is A_2 and X_2 is B_2, then $f_2 = m_2 X_1 + n_2 X_2 + q_2$.

where: m_1, n_1, q_1 and m_2, n_2, q_2 are the parameters of the output function.

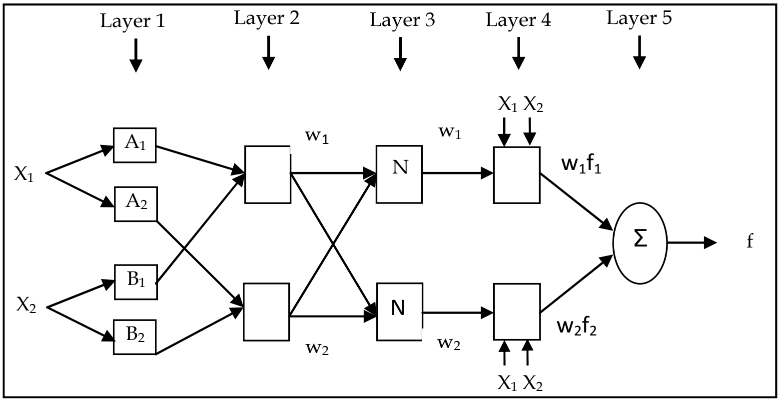


Fig. 7. Structure of the proposed ANFIS model

The architecture of the proposed (ANFIS), it contains five layers where the node functions in the same layer are of the same function family. Inputs, outputs and implemented mathematical models of the nodes of each layer are explained below.

Layer 1: The node function of every node *i* in this layer take the form:

$$O_i^1 = \mu A_i(X) \tag{8}$$

where X is the input to node i, μA_i is the membership function (which can be triangular, trapezoidal, gaussian functions or other shapes) of the linguistic label A_i associated with this node and O_i is the degree of match to which the input X satisfies the quantifier A_i. In the current study, the Gaussian shaped MFs defined below are utilized.

$$\mu A_i(X) = exp\left\{-\frac{1}{2}\frac{(X-c_i)^2}{\sigma_i^2}\right\} \tag{9}$$

where $\{c_i, \sigma_i\}$ are the parameters of the MFs governing the Gaussian functions. The parameters in this layer are usually referred to as premise parameters.

Layer 2: Every node in this layer multiplies the incoming signals from layer 1 and sends the product out as follows,

$$w_i = \mu A_i(X_1) \times \mu B_i(X_2), i = 1,2 \tag{10}$$

where the output of this layer (w_i) represents the firing strength of a rule.

Layer 3: Every node *i* in this layer is a node labeled N, determine the ratio of the *i*-th rule's firing strength to the sum of all rules' firing strengths as:

$$w_i^- = \frac{w_i}{w_1 + w_2} \tag{11}$$

where the output of this layer represent the normalized firing strengths.

Layer 4: Every node *i* in this layer is an adaptive node with a node function of the form:

$$O_i^4 = w_i^- f_i = w_i^- (m_i X_1 + n_i X_2 + q_i), i = 1,2 \tag{12}$$

where w_i^- is the output to layer 3, and $\{m_i, n_i, q_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: There is only a single node in this layer that computes the overall output as the weighted average of all incoming signals from layer 4 as:

$$O_i^5 = \sum_i w_i^- f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1,2 \tag{13}$$

3.2 Learning process

As mentioned earlier, both the premise (non-linear) and consequent (linear) parameters of the ANFIS should be tuned, utilizing the so-called learning process, to optimally represent the factual mathematical relationship between the input space and output space. Normally, as a first step, an approximate fuzzy model is initiated by the system and then improved through an iterative adaptive learning process. Basically, ANFIS takes the initial fuzzy model and tunes it by means of a hybrid technique combining gradient descent back-propagation and mean least-squares optimization algorithms. At each epoch, an error measure, usually defined as the sum of the squared difference between actual and desired output, is reduced. Training stops when either the predefined epoch number or error rate is obtained. There are two passes in the hybrid learning procedure for ANFIS. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent. When the values of the premise parameters are learned, the overall output (*f*) can be expressed as a linear combination of the consequent parameters (Jang, 1993):

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = w_1^- f_1 + w_2^- f_2 \\ &= (w_1^- X_1) m_1 + (w_1^- X_2) n_1 + (w_1^-) q_1 + (w_2^- X_2) m_2 + (w_2^- X_2) n_2 + (w_2^-) q_2 \end{aligned} \tag{14}$$

which is linear in the consequent parameters m_1, n_1, q_1, m_2, n_2 and q_2.

4. Cases studies

There are two case studies considered in this chapter:

1. Predicting of shear strength of ferrocement members using ANN and ANFIS.

2. Predicting of shear strength of concrete beams reinforced with FRP bars using ANN and ANFIS.

4.1 Case study 1

In this study the back-propagation neural networks (BPNN) model and adaptive neuro-fuzzy inference system (ANFIS) are utilized to predict the shear strength of ferrocement members. A database of the shear strength of ferrocement members obtained from the literature alongside the experimental study conducted by the author is used for the development of these models. The models are developed within MATLAB using BPNN and Sugeno ANFIS.

4.1.1 Review of shear strength of ferrocement members

In recent years, ferrocement has been widely accepted and utilized. Research and development on ferrocement has progressed at a tremendous pace. Many innovative applications are being explored and constructed throughout the world. The application of ferrocement in low cost housing is well known. However, as ferrocement elements are thin, their use for roofing and exterior walls raises doubts regarding the thermal comfort inside the building (Naaman, 2000). Ferrocement is a composite material constructed by cement mortar reinforced with closely spaced layers of wire mesh (Naaman, 2000; Shah, 1974). The ultimate tensile resistance of ferrocement is provided solely by the reinforcement in the direction of loading. The compressive strength is equal to that of the unreinforced mortar. However, in case of flexure and shear, the analysis and design of ferrocement elements is complex and are based primarily on the reinforced concrete analysis using the principles of equilibrium and compatibility.

Few methods have been proposed for the estimation of the shear strength of ferrocement specimens. One of these methods is considered in this study which is given by Rao et al., (2006). They proposed an empirical expression to estimate the shear strength of ferrocement elements by considering the shear resistance of ferrocement elements as the sum of shear resistance due to mortar and reinforcement. The shear resistance of ferrocement element (V_u) was given as:

$$\frac{V_u}{b.d} = \frac{\sqrt{f_c'}}{a/d}\left\{0.0856 + 0.0028\frac{v_f f_y}{\sqrt{f_c'}}\right\} \tag{15}$$

4.1.2 ANN for predicted the shear strength of ferrocement members

An artificial neural network was developed to predict the shear strength of ferrocement. This section describes the data selection for training and testing patterns, the topology of the constructed network, the training process and the verification of the neural network results. A relative importance is carried out which is based on the artificial neural network predictions. Finally, the results of the shear strength of ferrocement members predicted by BPNN and ANFIS are compared with the results of the experimental program and empirical method. The empirical method was proposed by (Rao et al., 2006).

4.1.2.1 Selection of the training and testing patterns

The experimental data that are used to train the neural network are obtained from literature (Mansur & Ong, 1987; Mashrei, 2010; Rao et al., 2006) as shown in Table A in appendix. The data used to build the neural network model should be divided into two subsets: training set and testing set. The testing set contains approximately 13% from total database. The training phase is needed to produce a neural network that is both stable and convergent. Therefore, selecting what data to use for training a network is one of the most important steps in building a neural network model. The total numbers of 69 test specimens was utilized. The training set contained 60 specimens and the testing set was comprised of 9 specimens.

Neural networks interpolate data very well. Therefore, patterns chosen for training set must cover upper and lower boundaries and a sufficient number of samples representing particular features over the entire training domain (Rafiq et al., 2001).An important aspect of developing neural networks is determining how well the network performs once training is complete. The performance of a trained network is checked by involving two main criteria:

1. How well the neural network recalls the predicted response from data sets used to train the network (called the recall step). A well trained network should be able to produce an output that deviates very little from desired value.
2. How well the network predicts responses from data sets that were not used in the training (called the generalization step). Generalization is affected by three factors: the size and the efficiency of the training data set, the architecture of the network, and the physical complexity of the problem. A well generalized network should be able to sense the new input patterns.

To effectively visualize how well a network performs recall and generalization steps, the learning curve is generated which represents the mean square error (MSE) for both the recall of training data sets and generalization of testing set with the number of iteration or epoch. The error between the training data sets and the generalization of testing sets should converge upon the same point corresponding to the best set of weight factors for the network.

4.1.2.2 Input and output layers

In the developed neural network model there is an input layer, where input data are presented to the network, and an output layer of one neuron representing the shear strength of ferrocement member. In this study the parameters which may be introduced as the components of the input vector consist of six inputs: the total depth of specimens cross

Parameters	Range
Width of specimens (b) (mm)	100-200
Total depth of specimens (d) (mm)	25-50
Shear span to depth ratio (a/d)	1-7
Compressive strength of mortar (f_c')	26.5-44.1
yield strength of wire mesh (f_y) (MPa)	380-410
Volume fraction of wire mesh (v_f) %	0-5.7

Table 1. Range of parameters in the database

section (d), the width of specimens cross section (b),yield tensile strength of wire mesh reinforcement (f_y), cylinder compressive strength of mortar (fc'), total volume fraction of wire mesh (v_f) and shear span to depth ratio (a/d). The shear strength of ferrocement member represents the target variable. Table 1 summarizes the ranges of each different variable.

4.1.2.3 Normalizing input and output data sets

Normalization (scaling down) of input and output data sets within a uniform range before they are applied to the neural network is essential to prevent larger numbers from overriding smaller ones, and to prevent premature saturation of hidden nodes, which impedes the learning process. The limitation of input and output values within a specified range are due to the large difference in the values of the data provided to the neural network. Besides, the activation function used in the back-propagation neural network is a hyperbolic tangent function, the lower and upper limits of this function are -1 and +1 respectively. In this study Eq. 5 mentioned above is used to normalize the input and output parameters. That equation gives the required results with a certain mean square error by a small number of epochs.

4.1.2.4 Number of hidden layers and nodes in each hidden layer

The network is tested with an increasing number of nodes in hidden layer. It is found that one-hidden layer network with four nodes gives the optimal configurations with minimum mean square error (MSE). As an activation function, a hyperbolic tangent function is selected for the hidden layer and a purelin function is used for the output layer.

In this study the initial weights are randomly chosen. The network has been trained continually through updating weights until the final error achieved is $8.48*10^{-4}$.

Fig. 8 shows the performance for training and generalization (testing) sets using resilient back-propagation training algorithm, the network is trained for 420 epochs to check if the performance (MSE) for either training or testing sets might diverge. The network performance with resilient back-propagation training algorithm have been tested for training and generalizing patterns, as shown in Fig. 9 (a) and (b). A good agreement has been noted in the predicted values compared with the actual (targets) values.

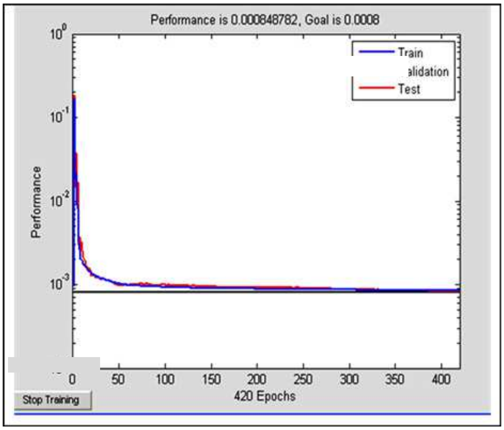
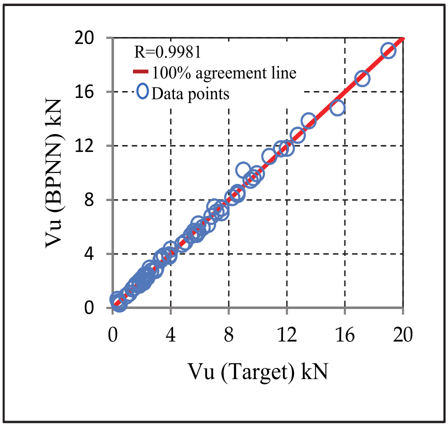
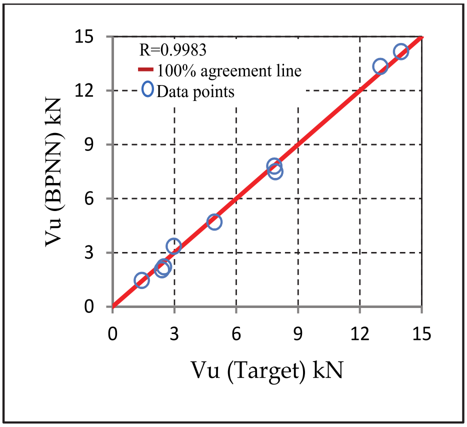


Fig. 8. Convergence of the BPNN for training and testing sets



(a) For training pattern



(b) For testing pattern

Fig. 9. Comparison between BPNN results and target results

4.1.2.5 Relative importance

Once the artificial neural network has been trained, a relative importance is used to investigate the influence of the various parameters on the shear strength. The effect of each parameter on the shear strength of ferrocement is clear in Table 2. After training all the data sets with the final model, the relative importance of each input variable is evaluated. The methodology suggested by Garson, (1991) is used. The relative importance of the various input factors can be assessed by examining input-hidden-output layer connection weights. This is carried out by partitioning the hidden-output connection weights into components connected with each input neuron. Table 2 lists the relative importance of the input variables in the BPNN model. It can be observed that for shear strength of the ferrocement member, the shear span to depth ratio ($^{a}/_{d}$) is the most important factor among the input variables and volume fraction of wire mesh is the second most important factor comparing with the others. Therefore, it can be concluded that ($^{a}/_{d}$) ratio has the most influence on the shear strength of ferrocement.

Input variables	b (mm)	d (mm)	$f_c{}'$ (MPa)	f_y (MPa)	$^{a}/_{d}$	v_f (%)
RI (%)	7.11	20.0	8.89	5.28	38.32	20.4

Table 2. Relative importance (RI) (%) of BPNN model

4.1.3 Adaptive neural fuzzy inference system (ANFIS) model

In the developed ANFIS, six variables consisting of width (b) and depth (d) of the specimens, yield tensile strength of wire mesh reinforcement (f_y), cylinder compressive strength of mortar ($f_c{}'$), total volume fraction of wire mesh (v_f) and shear span to depth ratio ($^{a}/_{d}$) are selected as input variables to predict the shear strength of ferrocement members, which is the target variable. In this investigation the subtractive clustering technique introduced by (Chiu, 1994)with (genfis2) function was used. Given separate sets of input and output data, the genfis2 uses a subtractive clustering method to generate a Fuzzy Inference System (FIS). When there is only one output, genfis2 may be used to generate an initial FIS for ANFIS training by first implementing subtractive clustering on the data. The genfis2 function uses the subclust function to estimate the antecedent membership functions and a set of rules. This function returns an FIS structure that contains a set of fuzzy rules to cover the feature space (Fuzzy Logic Toolbox, 2009). For a given set of data, subtractive clustering method was used for estimating the number of clusters and the cluster centers in a set of data. It assumes each data point is a potential cluster center and calculates a measure of the potential for each data point based on the density of surrounding data points. The algorithm selects the data point with the highest potential as the first cluster center and then delimits the potential of data points near the first cluster center. The algorithm then selects the data point with the highest remaining potential as the next cluster center and delimits the potential of data points near this new cluster center. This process of acquiring a new cluster center and delimiting the potential of surrounding data points repeats until the potential of all data points falls below a threshold. The range of influence of a cluster center in each of the data dimensions is called cluster radius. A small cluster radius will lead to finding many small clusters in the data (resulting in many rules) and vice versa (Jang, 1997; Jonic', 1999). Membership functions (MFs) and numbers are appropriately decided when testing data set.

4.1.3.1 Database

The adaptive neuro-fuzzy inference system model is developed to predict the shear strength of ferrocement members. The same database of (69) specimens as in the previous BPNN model is used for the development of this model. The total data is divided at random into two groups (training data set, and testing data set), as shown in Table A in Appendix.

4.1.3.2 Modeling and results

The ANFIS model is developed to predict shear strength of ferrocement specimens with MFs of type (gussmf) for all input variables and linear for the output. The number of MFs assigned to each input variable is chosen by trial and error. After training and testing, the

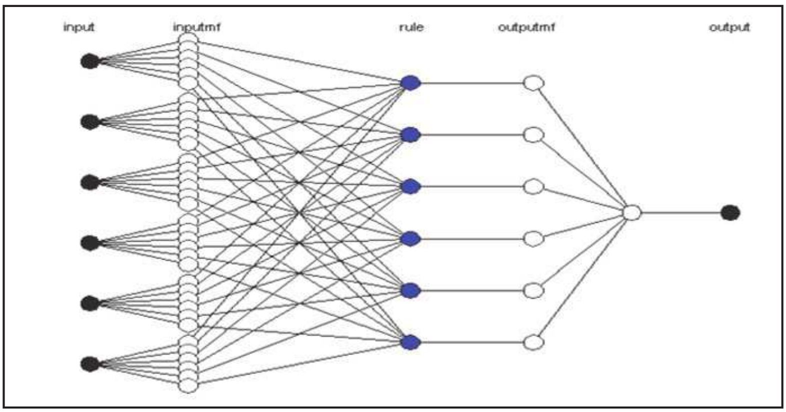


Fig. 10. Structure of the proposed ANFIS model

number of MFs is fixed as six MFs for each input variable. This is chosen when the ANFIS model reaches an acceptable satisfactory level. The structure of ANFIS model is developed as shown in Fig. 10. The basic flow diagram of computations in ANFIS is illustrated in Fig. 11. A comparison between the prediction from ANFIS and target value for each of training and testing data set is shown in Fig. 12(a) and (b) respectively. The predictions appear to be quite good with correlation coefficient R approaches one.

4.1.4 Comparison between experimental and theoretical results

The predictions of shear strength of ferrocement members as obtained from BPNN, ANFIS, and the empirical available method (Eq.15) (Rao et al., 2006) are compared with the experimental results and shown for both training and testing sets in Figs.13 and 14 and Table 3 . In Table 3 the ratios of experimental (V_e) to theoretical predictions of the shear strength (V_i) of the ferrocement specimens are calculated. The theoretical predications include those obtained by BPNN (V_1), ANFIS (V_2), and empirical method (Eq.15) (V_3). The average and the standard deviation of the ratios V_e/V_i are given in this table for both training and testing set. It can be seen that BPNN and ANFIS models give average values of V_e/V_1 and V_e/V_2 of 1.01 and standard deviations of 0.14 and 0.13, respectively for training set and the average values of V_e/V_1 and V_e/V_2 of 1.03 and standard deviations of 0.09 and 0.08, respectively for testing set , which are better than the values obtained for the empirical method. Figs. 13 and 14 confirm the same conclusion the predictions of BPNN and ANFIS

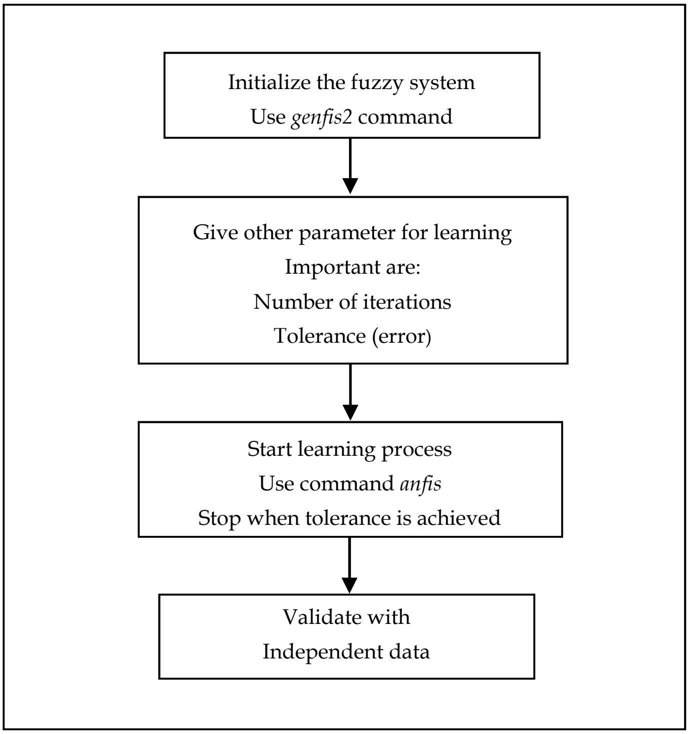
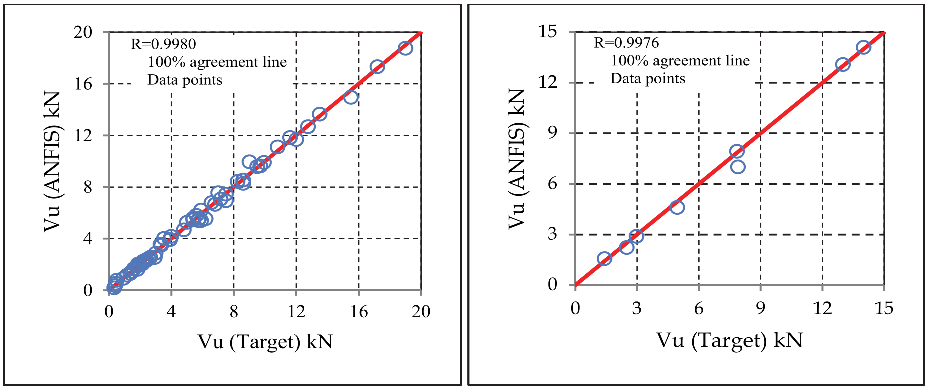


Fig. 11. The basic flow diagram of computations in ANFIS

models are better than those of the empirical method. Also in Table 3 the correlation coefficient R of predicted shear strength by BPNN, ANFIS, and the empirical method are summarized. As shown in Table 4, both ANFIS and BPNN produce a higher correlation coefficient R as compared with the empirical method. Therefore, the BPNN as well as ANFIS can serve as reliable and simple tools for the prediction of shear strength of ferrocement.



(a) For training pattern (b) For training pattern

Fig. 12. Comparison between ANFIS results and target results

Specimens	No.	Average of of V_e / V_i			STDEV of V_e / V_i		
		$\frac{V_e}{V_1}$	$\frac{V_e}{V_2}$	$\frac{V_e}{V_3}$	$\frac{V_e}{V_1}$	$\frac{V_e}{V_2}$	$\frac{V_e}{V_3}$
Training set	60	1.01	1.01	1.21	0.14	0.13	0.27
Testing set	9	1.03	1.03	1.23	0.09	0.08	0.31

Table 3. Comparison between experimental and predicted results for training and testing sets

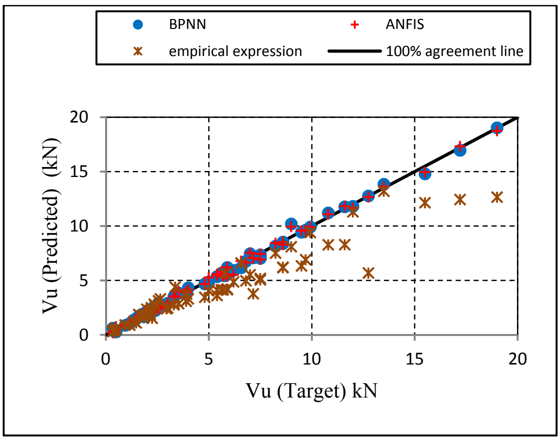


Fig. 13. Comparison experimental and predicted values for training data Set

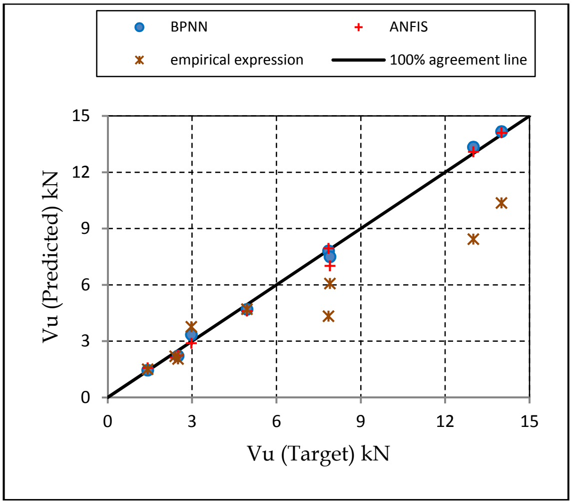


Fig. 14. Comparison experimental and predicted values for testing data Set

Type	Correlation R	
	Training	Testing
BPNN	0.9981	0.9983
ANFIS	0.9980	0.9976
Empirical Method	0.9500	0.9600

Table 4. Comparison summary of correlation R

4.2 Case study 2

In this part the PBNN and ANFIS models are developed to predict the shear strength of concrete beams reinforced with FRP bars. A database from tests on concrete beams reinforced with FRP bars obtained from the review of literature is used in this study. The structure of ANN and ANFIS models and the results of this study will be described below.

4.2.1 Review on shear strength of concrete beams reinforced with FRP bars

An FRP bar is made from filaments or fibers held in a polymeric resin matrix binder. The FRP Bar can be made from various types of fibers such as Glass (GFRP) or Carbon (CFRP). FRP bars have a surface treatment that facilitates a bond between the finished bar and the structural element into which they are placed (Bank, 2006).

During the last two decades, fiber reinforced polymer (FRP) materials have been used in a variety of configurations as an alternative reinforcement for new and strengthening civil engineering structures and bridges. The attractiveness of the material lies mainly in their high corrosion resistance, high strength and fatigue resistance. In some cases, the non-magnetic characteristics became more important for some special structures. An important application of FRP, which is becoming more popular (Tan, 2003, as cited in Al-Sayed et at., 2005a) is the use of FRP for reinforcement in concrete structures. The use of FRP in concrete structures include: (a) the internal reinforcing (rod or bar) which is used instead of the steel wire (rod) equivalent; and (b) the external bonded reinforcement, which is typically used to repair/strengthen the structure by plating or wrapping FRP tape, sheet or fabric around the member (Wu & Bailey, 2005).

There are fundamental differences between the steel and FRP reinforcements: the latter has a lower modulus of elasticity, the modulus of elasticity for commercially available glass and aramid FRP bars is 20 to 25 % that of steel compared to 60 to 75 % for carbon FRP bars (Bank, 2006) linear stress–strain diagram up to rupture with no discernible yield point and different bond strength according to the type of FRP product. These characteristics affect the shear capacity of FRP reinforced concrete members. Due to the relatively low modulus of elasticity of FRP bars, concrete members reinforced longitudinally with FRP bars experience reduced shear strength compared to the shear strength of those reinforced with the same amounts of steel reinforcement.

Some of empirical equations have been developed to estimate shear strength of concrete beams reinforced with FRP. Most of the shear design provisions incorporated in these codes and guides are based on the design formulas of members reinforced with conventional steel considering some modifications to account for the substantial differences between FRP and steel reinforcement. These provisions use the well-known $V_c + V_s$ method of shear design, which is based on the truss analogy. This section reviews the concrete shear strength of members longitudinally reinforced with FRP bars, V_{cf}, as recommended by the American Concrete Institute (ACI 440.1R-03, 2003), Tureyen and Frosch Equation (2003), and the proposed equation by El-Sayed et al. (2005a).

4.2.1.1 American Concrete Institute (ACI 440.1R-03)

The equation for shear strength proposed by the American Concrete Institute (ACI 440.1R-03), can be expressed as follows:

$$V_{cf} = \frac{\rho_f E_f}{90\beta_1 f_c'}\left(\frac{\sqrt{f_c'}}{6} b_w d\right) \le \frac{\sqrt{f_c'}}{6} b_w d \tag{16}$$

4.2.1.2 Tureyen and Frosch equation (2003)

This equation was developed by Tureyen and Frosch, 2003. It was developed from a model that calculates the concrete contribution to shear strength of reinforced concrete beams. The equation was simplified to provide a design formula applicable FRP reinforced beams as follows:

$$V_{cf} = \frac{2}{5}\left(\frac{\sqrt{f_c'}}{6} b_w c\right) \tag{17}$$

where: $c = kd$= cracked transformed section neutral axis depth (mm).

$$k = \sqrt{2\rho_f n_f + (\rho_f n_f)^2 - \rho_f n_f} \tag{18}$$

4.2.1.3 El-Sayed et al. equation (2005a)

They applied the same procedure in ACI 440.1R-03 to derive Eq. 1 above, with some modification for proposing the Eq. below:

$$V_{cf} = 0.037\ (\frac{\rho_f E_f \sqrt{f_c'}}{\beta_1})^{1/3} b_w d \leq \frac{\sqrt{f_c'}}{6} b_w d \quad (19)$$

According to ACI 440.1R-03, the factor β_1 in the denominator of Eq. 3 is a function of the concrete compressive strength. It can be simply expressed by the following equation:

$$0.85 \geq \beta_1 = 0.85 - 0.007(f_c' - 28) \geq 0.65 \quad (20)$$

4.2.2 Shear strength database

From the review of literature (Deitz, et al., 1999; El-Sayed et al. , 2005b, 2006a, 2006b, 2006c; Gross et al., 2003, 2004; Omeman et al., 2008; Razaqpur et al., 2004; Tariq & Newhook, 2003; Tureyen & Frosch, 2002, 2003; Wegian & Abdalla , 2005; Yost et al., 2001), a number (74) of shear strength tests are used for developing the ANN and ANFIS as shown in Table B in appendix. All specimens were simply supported and were tested in three-point loading. The main reinforcement of all specimens is FRP. All specimens had no transverse reinforcement and failed in shear. These data are divided into two sets: a training set containing 64 members, and testing set comprised of 10 members. Six input variables are selected to build the ANN and ANFIS models. These variables are width (b_w), and depth (d) of the beams, modulus of elasticity of FRP (E_f), compressive strength of concrete (f_c'), reinforcement ratio of FRP (ρ_f) and the shear span to depth ratio ($^a/_d$). The output value is the shear strength of concrete beams reinforced with FRP bars. Table 5 summarizes the ranges of each different variable.

Parameters	Range
Width of beams (b_w) mm	89-1000
Effective depth of beams (d) mm	143-360
Shear span to depth ratio ($^a/_d$)	1.3-6.5
Compressive strength of concrete (f_c') MPa	24-81
Modulus of elasticity of FRP (E_f) (GPa)	37-145
Reinforcement ratio of FRP (ρ_f)	0.25-2.63

Table 5. Summarizes the ranges of the different variables.

4.2.3 ANN model and results

ANN is used to investigate the shear strength of concrete beams reinforced with FRP bars. The configuration and training of neural networks is a trail-and-error process due to such undetermined parameters as the number of nodes in the hidden layer, and the number of training patterns. In the developed ANN, there is an input layer, where six parameters are presented to network and an output layer, with one neuron representing shear strength of concrete beams reinforced with FRP bars. One hidden layer as intermediate layer is also included. The network with one hidden layer and four nodes in the hidden layer gave the optimal configuration with minimum mean square error (MSE).

The back-propagation neural network model used for this study is trained by feeding a set of mapping data with input and target variables as explained previously. After the errors are minimized, the model with all the parameters including the connection weights is tested with a separate set of "testing" data that is not used in the training phase.

The network has trained continually through updating of the weights until error goal of $15.1*10^{-4}$ is achieved. Fig. 15 shows the performance for training and generalization (testing). A resilient back propagation training algorithm is used to train the network, for 800 epochs to check if the performance (MSE) for either training or testing sets might diverge.

The network performance with resilient back propagation training algorithm have been tested for training and testing patterns, as shown in Fig. 16 (a) and (b). A good agreement has been noted in the predicting values compared with the actual (targets) values.

Based on the same idea used to study the effect of the parameters on shear strength of ferrocement members, the effect of each parameter used in the input layer on shear strength of concrete beams reinforced with FRP bars is investigated. Table 6 lists the relative importance of the input variables in BPNN model. It can be observed that for shear strength of concrete beams reinforced with FRP, the shear span to depth ratio($^{a}/_{d}$) is also the most important factor among the input variables. This result is very match with the experimental results of many papers published in this field.

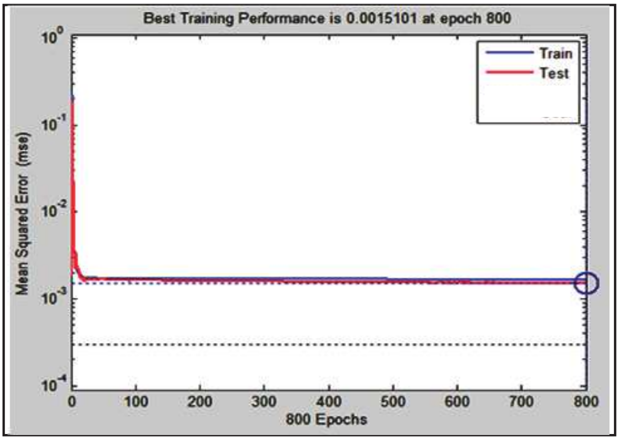
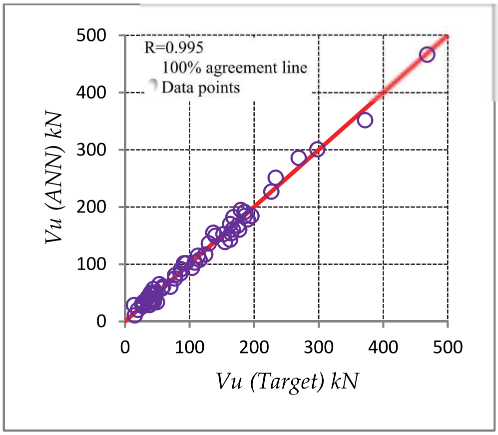
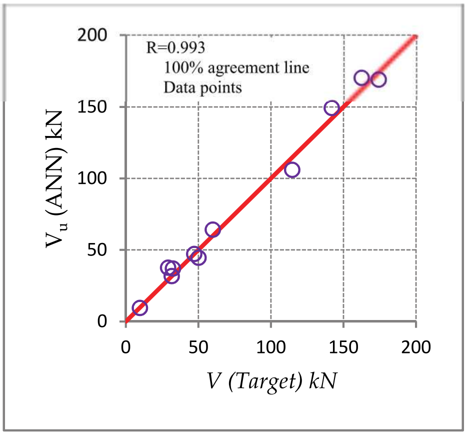


Fig. 15. Convergence of the BPNN for training and testing sets

Input variables	b_w (mm)	d (mm)	$f_c{}'$ (MPa)	E_f (MPa)	$^{a}/_{d}$	ρ_f (%)
RI (%)	24.76	18.26	11.11	5.23	37.50	3.19

Table 6. Relative importance (RI) (%) of BPNN model





(a) For training pattern (b) For training pattern

Fig. 16. Comparison between BPNN results and target results

4.2.4 ANFIS model and results

The same technique used to build the ANFIS to predict shear strength of ferrocement members is used to build of ANFIS to predict the shear strength of concrete beams reinforced with FRP bars. Fig. 17 presents the structure of an adaptive neuro-fuzzy inference system developed to predict shear strength of concrete beams reinforced with FRP bars. The membership functions (MFs) of type (Gauss) for all input variables and linear for output present the best prediction in this study. The number of MFs assigned to each input variable is chosen by trial and error. After training and testing the number of MFs was fixed at two MFs for each input variable, when the ANFIS model reaches an acceptable satisfactory level. A comparison between the predictions from ANFIS and target value for both the training and testing data set is presented in Fig. 18(a) and(b) respectively. A good agreement has been noted in the predicting values compared with the experimental (target) values with reasonably high correlation R.

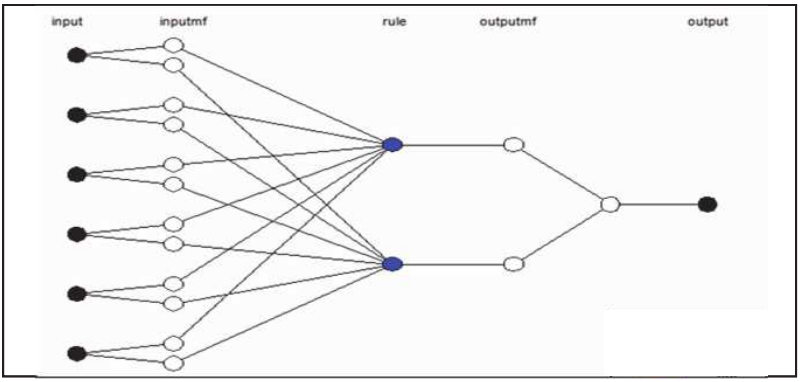
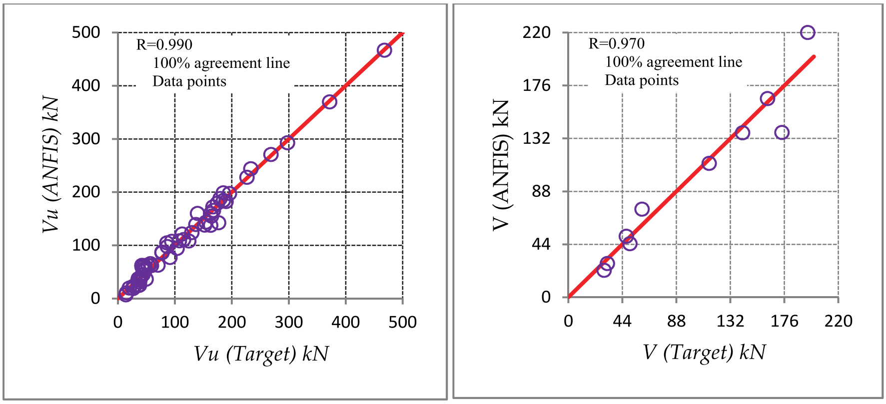


Fig. 17. Structure of the proposed ANFIS model



(a) For training pattern (b) For training pattern

Fig. 18. Comparison between BPNN results and target results

4.2.5 Comparison between experimental and theoretical results

The predictions of shear strength of beams reinforced with FRP as that obtained from BPNN, ANFIS, ACI 440.1R-03, Tureyen and Frosch's equation, and the proposed equation by El-Sayed et al. (2005a), are compared with the experimental results and shown for both training and testing sets in Figs. 19 and 20 and Table 7.

In Table 6 the ratios of experimental (V_e) to theoretical (V_i) predictions of the shear strength of beams reinforced with FRP are calculated, the theoretical predictions include those obtained by BPNN (V_1), ANFIS (V_2), proposed equation by El-Sayed et al. (V_3), ACI 440.1R-03 (V_4), and Tureyen and Frosch's equation (V_5). The average and the standard deviation of the ratios V_e/V_i are also given in this table. It can be seen that the BPNN and ANFIS models give average values for the testing set of V_e/V_1 and V_e/V_2 of 0.97 and 1.03 and standard deviations of 0.1 and 0.167 respectively which are much better than the values obtained from other methods as shown in table 7. Figs. 19 and 20 confirm the same conclusion that the predictions of the ANN and ANFIS models are better than those of the other methods.

Also in Table 8 the correlation coefficient R of predicted shear strength that was evaluated by BPNN, ANFIS and the other methods are summarized. As shown in Table 8, the BPNN and ANFIS produces a higher correlation coefficient R as compared with the other methods. These results indicate that the BPNN and ANFIS is a reliable and simple model for predicting the shear strength of beams reinforced with FRP bars.

Specimens	No	Average of of V_e / V_i					STDEV of V_e / V_i				
		$\frac{V_e}{V_1}$	$\frac{V_e}{V_2}$	$\frac{V_e}{V_3}$	$\frac{V_e}{V_4}$	$\frac{V_e}{V_5}$	$\frac{V_e}{V_1}$	$\frac{V_e}{V_2}$	$\frac{V_e}{V_3}$	$\frac{V_e}{V_4}$	$\frac{V_e}{V_5}$
Training set	64	1.01	1.04	2.30	5.32	3.17	0.16	0.23	2.31	3.94	2.98
Testing set	10	0.96	1.03	2.01	3.93	2.73	0.103	0.17	1.72	1.62	2.27

Table 7. Comparison between experimental and Predicted results for training and testing sets

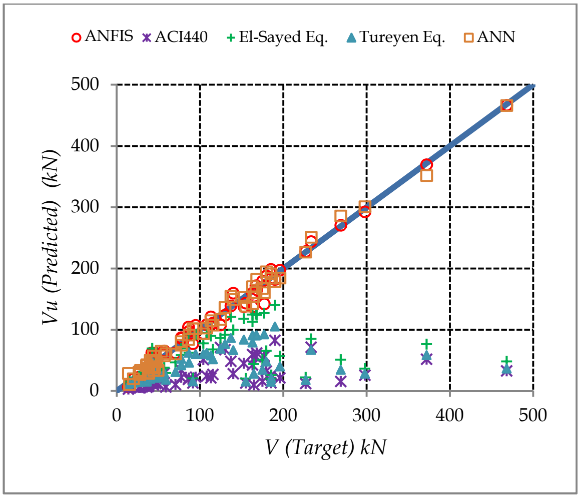


Fig. 19. Comparison experimental and predicted values for testing data set

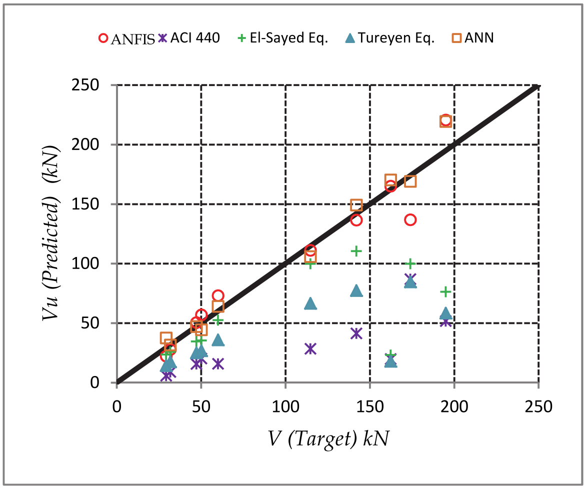


Fig. 20. Comparison experimental and predicted values for testing data set

Type	Correlation R	
	Training	Testing
ANN	0.995	0.993
ANFIS	0.99	0.97
El-Sayed's Eq.	0..32	0.63
ACI 440	0.51	0.78
Tureyen and Frosch's Eq.	0.37	0.69

Table 8. Comparison summary of correlation R

5. Conclusion

Two civil engineering applications are preformed using back-propagation neural network (BPNN)and adaptive neuro fuzzy inference system (ANFIS). The models were developed by predicting the shear strength of ferrocement members and the shear strength of concrete beams reinforced with fiber reinforced polymer (FRP) bars using BPNN and ANFIS based on the results of experimental lab work conducted by different authors. From the results of this study, the following conclusions can be stated:

1. BPNN and ANFIS have the ability to predict the shear strength of ferrocement members and the shear strength of concrete beams reinforced with FRP with a high degree of accuracy when they are compared with experimental and available methods results.
2. The relative importance of each input parameter is estimated using ANN. The relative importance study indicated that the predicted shear strength for both ferrocement and concrete beams with FRP by ANN models are in agreement with the underlying behavior of shear strength prediction based on the prior knowledge.
3. The ANN and ANFIS techniques offer an alternative approach to conventional techniques and, from them, some advantages can be obtained. Conventional models are based on the assumption of predefined empirical equations dependent on unknown parameters. However, in problems for which the modeling rules are either not known or extremely difficult to discover, such as in our problem, the conventional methods do not work well as shown in results. By using artificial neural network and the adaptive neuro fuzzy inference system, these difficulties are overcome since they are based on the learning and generalization from experimental data. ANN and ANFIS models can serve as reliable and simple predictive tools for the prediction of shear strength for both ferrocement and concrete beams with FRP of ferrocement members. Therefore, these models can be applied to solve most of civil engineering problems as a future research.

6. Nomenclature

V_u: Shear strength.
V_{cf}: The shear resistance of members reinforced with FRP bars as flexural reinforcement.
b: Width of the specimen.
d: Depth of the specimen.
v_f: Volume fraction of the mesh reinforcement ($100*A_{ls}/$ bd).
A_{ls}: Cross sectional area of the longitudinal reinforcing mesh
b_w: Width of the concrete specimen reinforced wih FRP
ρ_f: Reinforcement ratio of flexural FRP.
E_f: Modulus of elasticity of fiber reinforced polymers.
n_f: Ratio of the modulus of elasticity of FRP bars to the modulus of elasticity of concrete.
$f_c^{'}$: Compressive strength of concrete or mortar.
f_y: Yield strength of reinforcement (wire mesh or FRP).
a/d: Shear span to depth ratio.
β_1: Is a function of the concrete compressive strength.

6.1 Appendix

Test No.	b (mm)	d (mm)	f_c' (MPa)	f_y (MPa)	a/d	v_f %	V_u (kN)	Reference
1	100	40	35.20	410.00	1.00	1.80	8.60	*Mansur Ong*, 1987
2	100	40	35.20	410.00	1.50	1.80	5.40	
3	100	40	35.20	410.00	2.00	1.80	3.90	
4	100	40	35.20	410.00	2.50	1.80	3.00	
5	100	40	35.20	410.00	3.00	1.80	2.50	
6	100	40	35.20	410.00	1.00	2.72	10.80	
7	100	40	35.20	410.00	1.50	2.72	7.00	
8	100	40	35.20	410.00	2.00	2.72	5.70	
9	100	40	35.20	410.00	2.50	2.72	4.00	
10	100	40	35.20	410.00	3.00	2.72	3.30	
11	100	40	36.00	410.00	1.00	3.62	14.00	
12	100	40	36.00	410.00	1.50	3.62	9.70	
13	100	40	36.00	410.00	2.00	3.62	7.50	
14	100	40	36.00	410.00	2.50	3.62	5.90	
15	100	40	36.00	410.00	3.00	3.62	4.80	
16	100	40	36.00	410.00	1.00	4.52	17.20	
17	100	40	36.00	410.00	1.50	4.52	11.60	
18	100	40	36.00	410.00	2.00	4.52	8.60	
19	100	40	36.00	410.00	2.50	4.52	6.80	
20	100	40	36.00	410.00	3.00	4.52	5.60	
21	100	40	44.10	410.00	1.00	4.52	19.00	*Mansur & Ong, 1987*
22	100	40	44.10	410.00	1.50	4.52	13.00	
23	100	40	44.10	410.00	2.00	4.52	9.50	
24	100	40	44.10	410.00	2.50	4.52	7.50	
25	100	40	44.10	410.00	3.00	4.52	5.90	
26	100	40	26.50	410.00	1.00	4.52	15.50	
27	100	40	26.50	410.00	1.50	4.52	9.00	
28	100	40	26.50	410.00	2.00	4.52	7.90	
29	100	40	26.50	410.00	2.50	4.52	6.20	
30	100	40	26.50	410.00	3.00	4.52	5.00	
31	150	25	32.20	0	1.00	0	1.84	*Rao et al.*, 2006
32	150	25	32.20	380.00	1.00	2.85	8.24	
33	150	25	32.20	380.00	1.00	3.80	9.93	
34	150	25	32.20	380.00	1.00	4.75	12.00	

Test No.	b (mm)	d (mm)	f_c' (MPa)	f_y (MPa)	a/d	v_f %	V_u (kN)	Reference
35	150	25	32.20	380.00	1.00	5.70	13.50	
36	150	25	32.20	380.00	2.00	0	0.93	
37	150	25	32.20	380.00	2.00	2.85	3.92	
38	150	25	32.20	380.00	2.00	3.80	4.95	
39	150	25	32.20	380.00	2.00	4.75	5.79	
40	150	25	32.20	380.00	2.00	5.70	6.57	
41	150	25	32.20	0	3.00	0	0.49	
42	150	25	32.20	380.00	3.00	2.85	2.20	
43	150	25	32.20	380.00	3.00	3.80	2.55	
44	150	25	32.20	380.00	3.00	4.75	2.97	
45	150	25	32.20	380.00	3.00	5.70	3.36	
46	150	25	32.20	0	4.00	0	0.44	
47	150	25	32.20	380.00	4.00	2.85	1.60	
48	150	25	32.20	380.00	4.00	3.80	1.99	
49	150	25	32.20	380.00	4.00	4.75	2.35	
50	150	25	32.20	380.00	4.00	5.70	2.65	
51	150	25	32.20	0	5.00	0	0.40	
52	150	25	32.20	380.00	5.00	2.85	1.42	
53	150	25	32.20	380.00	5.00	3.80	1.86	
54	150	25	32.20	380.00	5.00	4.75	2.16	
55	150	25	32.20	380.00	5.00	5.70	2.40	
56	150	25	32.20	0	6.00	0	0.34	
57	150	25	32.20	380.00	6.00	2.85	1.37	
58	150	25	32.20	380.00	6.00	3.80	1.84	
59	150	25	32.20	380.00	6.00	4.75	2.15	
60	150	25	32.20	380.00	6.00	5.70	2.40	
61	200	50	33.80	390.00	7.00	0.25	1.16	Mashrei, 2010
62	200	50	33.80	390.00	7.00	0.50	1.47	
63	200	50	36.90	390.00	7.00	0.99	2.25	
64	200	50	40.40	390.00	3.00	0.25	2.94	
65	200	50	40.40	390.00	3.00	0.50	3.53	
66	200	50	40.40	390.00	3.00	0.99	7.16	
67	200	50	41.20	390.00	2.00	0.25	5.40	
68	200	50	41.20	390.00	2.00	0.50	7.85	
69	200	50	41.20	390.00	2.00	0.99	12.75	

Table A. Experimental data used to construct the BPNN and ANFIS for shear strength of ferrocement members

Test No.	b (mm)	d (mm)	f_c' (MPa)	ρ_f %	E_f (Gpa)	a/d	V_u (kN)	Reference
1	1000	165.3	40	0.39	114	6.05	140	El-Sayed et al., 2005b
2	1000	159	40	1.7	40	6.29	142	
3	1000	165.3	40	0.78	114	6.05	167	
4	1000	160.5	40	1.18	114	6.23	190	
5	1000	162.1	40	0.86	40	6.16	113	
6	1000	162.1	40	1.71	40	6.16	163	
7	1000	159	40	2.44	40	6.29	163	
8	1000	154.1	40	2.63	40	6.49	168	
9	250	326	44.6	1.22	42	3.07	60	El-Sayed et al., 2006a, 2006b
10	250	326	50	0.87	128	3.07	77.5	
11	250	326	50	0.87	39	3.07	70.5	
12	250	326	44.6	1.24	134	3.07	104	
13	250	326	43.6	1.72	134	3.07	124.5	
14	250	326	43.6	1.71	42	3.07	77.5	
15	250	326	63	1.71	135	3.07	130	
16	250	326	63	2.2	135	3.07	174	
17	250	326	63	1.71	42	3.07	87	
18	250	326	63	2.2	42	3.07	115.5	
19	200	225	40.5	0.25	145	2.67	36.1	Razaqpur et al., 2004
20	200	225	49	0.5	145	2.67	47	
21	200	225	40.5	0.63	145	2.67	47.2	
22	200	225	40.5	0.88	145	2.67	42.7	
23	200	225	40.5	0.5	145	3.56	49.7	
24	200	225	40.5	0.5	145	4.22	38.5	
25	127	143	60.3	0.33	139	6.36	14	Gross et al., 2004
26	159	141	61.8	0.58	139	6.45	20	
27	121	141	81.4	0.76	139	6.45	15.4	
28	160	346	37.3	0.72	42	2.75	59.1	
29	160	346	43.2	1.1	42	3.32	44.1	Tariq & Newhook, 2003
30	160	325	34.1	1.54	42	3.54	46.8	
31	130	310	37.3	0.72	120	3.06	47.5	
32	130	310	43.2	1.1	120	3.71	50.15	
33	130	310	34.1	1.54	120	3.71	57.1	
34	203	225	79.6	1.25	40.3	4.06	38	Gross et al., 2003
35	152	225	79.6	1.66	40.3	4.06	32.53	
36	165	224	79.6	2.1	40.3	4.08	35.77	
37	203	224	79.6	2.56	40.3	4.08	46.4	

Test No.	b (mm)	d (mm)	f_c' (MPa)	ρ_f %	E_f (Gpa)	a/d	V_u (kN)	Reference
38	457	360	39.7	0.96	40.5	3.39	108.1	Tureyen & Frosch, 2002
39	457	360	40.3	0.96	47.1	3.39	114.8	
40	457	360	39.9	0.96	37.6	3.39	94.7	
41	457	360	42.3	1.92	40.5	3.39	137	
42	457	360	42.5	1.92	37.6	3.39	152.6	
43	457	360	42.6	1.92	47.1	3.39	177	
44	229	225	36.3	1.11	40.3	4.06	38.13	Yost et al., 2001
45	229	225	36.3	1.66	40.3	4.06	44.43	
46	279	225	36.3	1.81	40.3	4.06	45.27	
47	254	224	36.3	2.05	40.3	4.08	45.1	
48	229	224	36.3	2.27	40.3	4.08	42.2	
49	178	279	24.1	2.3	40	2.69	53.4	
50	178	287	24.1	0.77	40	2.61	36.1	
51	178	287	24.1	1.34	40	2.61	40.1	
52	305	157.5	28.6	0.73	40	4.5	26.8	Deitz et al., 1999
53	305	157.5	30.1	0.73	40	5.8	28.3	
54	305	157.5	28.2	0.73	40	5.8	28.5	
55	305	157.5	27	0.73	40	5.8	29.2	
56	305	157.5	30.8	0.73	40	5.8	27.6	
57	150	150	34.7	1.13	134	1.55	185.2	Omeman et al.,2008
58	150	150	38.9	1.13	134	1.83	154.9	
59	150	150	37.4	1.7	134	1.83	162.3	
60	150	150	40.6	1.13	134	2.33	91.5	
61	150	150	39.6	2.26	134	1.83	185.5	
62	150	250	41.7	1.35	134	1.41	298.1	
63	150	350	37.6	1.21	134	1.36	468.2	
64	150	150	63.1	1.13	134	1.83	226.9	
65	250	326	40	0.78	134	1.69	179.5	Al-Sayed, 2006
66	250	326	40	0.78	40	1.69	164.5	
67	250	326	40	1.24	40	1.69	175	
68	250	326	40	1.24	134	1.69	195	
69	250	326	40	1.71	134	1.69	233.5	
70	250	326	40	1.71	40	1.69	196	
71	250	326	40	1.24	134	1.3	372	
72	250	326	40	1.24	40	1.3	269	
73	1000	112	60	0.95	41.3	8.93	42.6	Wegian& Abdalla, 2005
74	1000	162	60	0.77	41.3	6.17	86.1	

Table B. Experimental data used to construct the BPNN and ANFIS for shear strength of concrete beams reinforced with FRP.

7. References

Adeli, H. & Park, H. (1995). A Neural Dynamic Model for Structural Optimization-Theory. *Journal of Computer and Structure*, Vol.57, No.3, pp. 383–390, ISSN 0045-7949

Abudlkudir, A.; Ahmet, T.& Murat, Y. (2006). Prediction of Concrete Elastic Modulus Using Adaptive Neuro-Fuzzy Inference System. *Journal of Civil Engineering and Environmental Systems*, Vol.23, No.4, pp.295–309, ISSN 1028-6608

Akbuluta, S.; Samet, H. & Pamuk S. (2004). Data Generation for Shear Modulus and Damping Ratio in Reinforced Sands Using Adaptive Neuro-Fuzzy Inference System. *Journal of Soil Dynamics and Earthquake Engineering*, Vol. 24, No.11, pp. 805–814, ISSN 0267-7261

Alkhrdaji, T.; Wideman, M.; Belarbi, A. & Nanni, A. (2001). Shear Strength of GFRP RC Beams and Slabs, *Proceedings of the International Conference, Civil Construction International Conference (CCC) 2001, Composites in Construction*, pp. 409-414, Porto/Portugal

Bank .L. (2006). *Composites for Construction: Structural Design with FRP Materials*, John Wiley, ISBN 0471681261, New Jersey

Baughman, D. & Liu, Y. (2005). *Neural Network in Bioprocessing and Chemical Engineering*. Academic Press,. ISBN 0120830302. San Diego, CA

Carpenter, W.& Barthelemy, J. (1994). Common Misconceptions about Neural Networks as Approximators. *Journal of Computing in Civil Engineering*, Vol.8, No.3, pp. 345-358

Chen, S. & Shah, K. (1992). Neural Networks in Dynamic Analysis of Bridges. Proceedings, 8th Confernce. *Computing in Civil Engineering and Geographic Information System Symposium* ASCE, PP.1058–1065, New York, USA.

Chiu S. (1994). Fuzzy Model Identification Based on Cluster Estimation. *Journal of Intelligent and Fuzzy System*, Vol.2, No.3, pp.267-278.

Cladera, A. & Mar A. (2004). Shear Design Procedure for Reinforced Normal and High-Strength Concrete beams Using Artificial Neural Networks. Part I: Beams Without Stirrups. *Journal Engineering Structure*, Vol.26, No.7 pp. 917-926, ISSN 0141-0296

Cladera, A. & Mar A. (2004). Shear Design Procedure for Reinforced Normal and High-Strength Concrete beams Using Artificial Neural Networks. Part II: Beams With Stirrups. *Journal Engineering Structure,* Vol. 26, No.7pp. 927-936, ISSN 0141-0296

Deitz, D.; Harik, I. & Gesund, H. (1999). One-Way Slabs Reinforced with Glass Fiber Reinforced Polymer Reinforcing Bars, *Proceedings of the 4th International Symposium, Fiber Reinforced Polymer Reinforcement for Reinforced Concrete Structures*, pp. 279-286, Maryland, USA

Eberhart, R. & Dobbins, R. (1990). *Neural Network PC Tools A Practical Guide*. Academic Press, ISBN0-12-228640-5, San Diego, CA

Eldin, N. & Senouci, A.(1995), A Pavement Condition-Rating Model Using Back Propagation Neural Networks. *Microcomputers in Civil Engineering,* Vol.10, No.6, pp. 433–441

El-Sayed, A.; El-Salakawy, E. & Benmokrane, B. (2004). Evaluation of Concrete Shear Strength for Beams Reinforced with FRP Bars, *5th Structural Specialty Conference of the Canadian Society for Civil Engineering, CSCE*, Saskatoon, Saskatchewan, Canada

El-Sayed, A.; El-Salakawy, E. & Benmokrane, B. (2005a). Shear Strength of Concrete Beams Reinforced with FRP Bars: Design Method, ACI- SP-230—54, pp.955-974

El-Sayed, A.; El-Salakawy, E. & Benmokrane, B. (2005b). Shear Strength of One-way Concrete Slabs Reinforced with FRP Composite Bars. *Journal of Composites for Construction*, ASCE, Vol.9, No.2, pp.147-157, ISSN 1090-0268

El-Sayed, A.; El-Salakawy, E. & Benmokrane, B. (2006a). Shear Strength of FRP Reinforced Concrete Beams without Transverse Reinforcement. *ACI Structural Journal*, Vol.103, No.2, pp.235-243, ISSN 0889-3241

El-Sayed, A.; El-Salakawy, E. & Benmokrane, B. (2006b). Shear Capacity of High-Strength Concrete Beams Reinforced with FRP Bars. *ACI Structural Journal,*Vol.103, No.3, pp.383-389, ISSN 0889-3241

El-Sayed, A. (2006c),Concrete Contribution to the Shear Resistance of FPR- Reinforced Concrete beams, PhD Thesis, Sherbrook University, Canada.

Feng, M. & Kim, J. (1998). Identification of a Dynamic System Using Ambient Vibration Measurements. *Journal of Applied Mech*anic, Vo.65, No.2, pp. 1010– 1023, ISSN 0021-8936

Feng, M. & Bahng, E. (1999). Damage Assessment of Jacketed RC Columns Using Vibration Tests. *Journal of Structure Engineering*, Vol.125, No.3, pp. 265–271, ISSN 0733-9445

Fonseca, E.; Vellasco, S. & Andrade S. (2008). A Neuro-Fuzzy Evaluation of Steel Beams Patch Load Behaviour. *Journal of Advances in Engineering Software*, Vol.39, No.7, pp.535-555, ISSN 0965-9978

Fuzzy Logic Toolbox User's Guide for Use with MATLAB 2009.

Gershenson C. Artificial Neural Networks for Beginners. Cognitive and Computing Sciences, University of Sussex, Available from, http:// cgershen@vub.ac.be

Garson, G. (1991). Interpreting Neural-Network Connection Weights. *AI Expert*, Vol.6, No.7, pp. 47-51, ISSN 0888-3785

Gagarin, N.; Flood, I., & Albrecht, P. (1994). Computing Truck Attributes with Artificial Neural Networks. *Journal of Computing in Civil Engineering*, Vol.8, No.2, ISSN 0887-3801

Guide for the Design and Construction of Concrete Reinforced with FRP Bars (ACI 440.1R-03), Reported by ACI Committee 440, 2003

Gross, S.; Dinehart, D.; Yost, J. & Theisz, P. (2004). Experimental Tests of High-Strength Concrete Beams Reinforced with CFRP Bars, *Proceedings of the 4th International Conference on Advanced Composite Materials in Bridges and Structures (ACMBS-4)*, Calgary, Alberta, Canada, July 20-23, 8p.

Gross, S. P.; Yost, J.; Dinehart, D. W.; Svensen, E. & Liu, N. (2003). Shear Strength of Normal and High Strength Concrete Beams Reinforced with GFRP Reinforcing Bars, Proceedings of the International Conference on High Performance Materials in Bridges, ASCE, 426-437.

Hajela, P. & Berke, L. (1991). Neurobiological Computational Models in Structural Analysis and Design. *Computers and Structures*, Vol.41, No.4, pp. 657-667, ISSN 0045-7949

Hamidian D. & Seyedpoor M. (2010). Shape Optimal Design of Arch Dams Using an Adaptive Neuro-Fuzzy Inference System and Improved Particle Swarm Optimization. *Jornal of Applied Mathematical Modelling*. Vol.34, No.6. pp.1574-1585.

Jang, S.; Sun T. & Mizutani E. (1997). *Neuro-Fuzzy and Soft Computing A Computational Approach to Learning and Machine intelligence*, Prentice Hall, Inc. ISBN 0132610663

Jang S. (1993). Adaptive network-based Fuzzy Inference System. *IEEE Journal*, Vol.23, No.3, PP.665-685, ISSN 0018-9472

Jeon J. (2007). Fuzzy and Neural Network Models for Analyses of Piles. PhD thesis, Civil Engineering, NCSU, USA.

Jonic', S.; Jankovic', T.; Gajic', V. & Popovic', D. (1999). Three Machine Learning Techniques for Automatic Determination of Rules to Control Locomotion. *Journal of IEEE*, Vol.46, No.3, pp.300-310, ISSN 0018-9294.

Lin. C. & Lee. C. (1996). *Neural Fuzzy Systems-A Neuro Fuzzy Synergism to Intelligent Systems*. Prentice Hall P T R. Upper Saddle River, N.J., ISBN 0-13-235169-2

Lin, J.; Hwang, M.; Becker, J. (2003). A Fuzzy Neural Network for Assessing the Risk of Fraudulent Financial Reporting. *Managerial Auditing Journal*, Vol.18, No.8, pp. 657-665, ISSN 0268-6902

Mamdani, E. & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man Machine Studies*, Vol.7, No.1, pp. 1-13, ISSN 00207373

Mansur, M. & Ong, K. (1987). Shear Strength of Ferrocement Beams. *ACI Structural Journal*, Vol.84, No.1, pp. 10-17.

Mansour, M.; Dicleli, M.; Lee, J. & Zhang, J. (2004). Predicting the Shear Strength of Reinforced Concrete Beams Using Artificial Neural Networks. *Journal of Engineering Structures*, Vol.26, No.6, pp.781–799, ISSN 0141-0296

Malhotra, R. & Malhotra, D. (1999). Fuzzy Systems and Neuro-Computing in Credit Approval. *Journal of Lending & Credit Risk Management*, Vol.81, No.11, pp. 24-37.

Mashrei, M. (2010). Flexure and Shear Behavior of Ferrocement Members: Experimental and Theoretical Study, PhD thesis, Civil Engineering, Basrah University, Iraq.

McCulloch and Pitts, W. (1943). A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics*, Vol.(5), pp. 115-133, ISSN 0092-8240

Mukherjee, A.; Deshpande, J. & Anmada, J. (1996). Prediction of Buckling Load of Columns Using Artificial Neural Networks. *Journal of . Structural Engineering,* Vol.122, No.11, pp. 1385–1387, ISSN 0733-9445

Naaman, A. *(2000. Ferrocement and Laminated Cementitious Composites*. Ann Arbort, Michigan, Techno Press 3000, USA 2000. ISBN 0967493900

Neural Network Toolbox User's Guide for Use with MATLAB, 2009

Omeman, Z.; Nehdi, M. & El-Chabib, H. (2008). Experimental Study on Shear Behavior of Carbon-Fiber-Reinforced Polymer Reinforced Concrete Short Beams without Web Reinforcement. *Canadian Journal of Civil Engineering*, Vol.35, No.1, pp.1-10.

Rafiq, M.; Bugmann, G. & Easterbrook, D. (2001). Neural Network Design for Engineering Applications, *Journal of Computers and Structures*, Vol.79, No. 17, pp.1541-1552.

Rao, C.; Rao, G. & Rao, R. (2006). An Appraisal of the Shear Resistance of Ferrocement Elements. *ASIAN Journal of Civil Engineering (Building and Housing)*, Vol.7, No.6, pp. 591-602.

Razaqpur, A.; Isgor, B.; Greenaway, S. & Selley, A. (2004). Concrete Contribution to the Shear Resistance of Fiber Reinforced Polymer Reinforced Concrete Members. *Journal of Composites for Construction*, ASCE, Vol.8, No.5, pp. 452-460,ISSN 1090-0268

Sanad, A. & Saka, M. (2001). Prediction of Ultimate Shear Strength of Reinforced Concrete Deep Beams using neural Networks. *Journal of Structural Engineering*, Vol.127, No.7, pp. 818-828, ISSN 0733-9445

Shah, S. (1974). New Reinforcing Materials in Concrete. *Journal of ACI*, Vol.71, No.5, pp. 257-262.

Sugeno, M.(1985). *Industrial applications of fuzzy control*, Elsevier Science Pub, ISBN0444878297, NY, USA

Topcu, I. & Sarıdemir M. (2007). Prediction of Compressive Strength of Concrete Containing Fly Ash Using Artificial Neural Networks and Fuzzy Logic. *Computational Materials Science*, Vol.41, No.3, pp.305-311, ISSN0927-0256

Tariq, M. & Newhook, J. (2003). Shear Testing of FRP reinforced Concrete without Transverse Reinforcement, *Proceedings of Canadian Society for Civil Engineering (CSCE)Anuual Conference*, Moncton, NB, Canada, 10p.

Tesfamariam, S. & Najjaran, H. (2007). Adaptive Network-Fuzzy Inferencing to Estimate Concrete Strength Using Mix Design. *Journal of Materials in Civil Engineering*, Vol.19, No.7, pp. 550-560, ISSN 0899-1561

Tully, S. (1997). Neural Network Approach for Predicting the Structural Behaviour of Concrete Slabs. M.Sc Thesis, College of Engineering and Applied Science, University of Newfoundland.

Turban, E. & Aronson, J. (2000). *Decision Support Systems and Intelligent Systems*, 6th edition, Prentice-Hall, Englewood Cliffs, NJ, ISBN: 0130894656.

Tureyen, A. & Frosch, R. (2002). Shear Tests of FRP-Reinforced Concrete Beams without Stirrups. *ACI Structural Journal*, Vol.99, No.4, pp.427-434, ISSN 0889-3241

Tureyen, A. & Frosch, R. (2003). Concrete Shear Strength: Another Perspective. *ACI Structural Journal*. Vol.100, No.5, pp. 609-615.

Waszczyszyn, Z.; Pabisek, E. & Mucha, G., (1998). Hybrid Neural Network/Computational Program to the Analysis of Elastic- Plastic Structures, *Neural networks in Mechanics of Structures and Materials*, Udine, Italy, pp. 19-23.

Wegian, F.& Abdalla, H. (2005). Shear Capacity of Concrete Beams Reinforced with Fiber Reinforced Polymers. *Journal of Composite Structures*, Vol.71, No.1, pp. 130–138, ISSN 0263-8223

Wu, Z. & Bailey, C. (2005). Fracture Resistance of a Cracked Concrete Beam Post Strengthened with FRP Sheets. *International Journal of Fracture*, Vol.135, No.(1-4), pp.35–49, ISSN 0376-9429

Yost, J.; Gross, S. & Dinehart, D. (2001). Shear Strength of Normal Strength Concrete Beams Reinforced with Deformed GFRP Bars. *Journal of Composites for Construction*, ASCE, Vol.5, No.4, pp. 268-275, ISSN 1090-0268

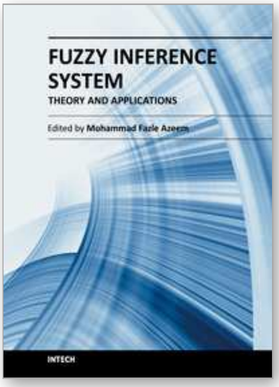
Zadeh L. (1965). Fuzzy sets. *Journal of Information and Control*, Vol.8, No.3, pp. 338-353.

Zadeh, L. Making Computers Think Like People. *IEEE Spectrum*. 1984; Vol.21, No.8 pp.26-32, ISSN 0018-9235

Zadih, L. (1993). Fuzzy Logic, Neural Networks and Soft Computing. *Microprocessing and Microprogramming,* Vol.38, No.1,pp.13, ISSN 0165-6074

Zadeh, L. (1994), Fuzzy Logic, Neural Networks and Soft Computing. Communication of the ACM, Vol.3, No.3, pp.77-84.

Zaho, J. & Bose, B. (2002). Evaluation of membership Functions for Fuzzy Logic Controlled Induction Motor Drive. *IEEE Journal*, Vo.1, No.pp.229-234, ISBN 0-7803-7474-6. S



Fuzzy Inference System - Theory and Applications
Edited by Dr. Mohammad Fazle Azeem

ISBN 978-953-51-0525-1
Hard cover, 504 pages
Publisher InTech
Published online 09, May, 2012
Published in print edition May, 2012

This book is an attempt to accumulate the researches on diverse inter disciplinary field of engineering and management using Fuzzy Inference System (FIS). The book is organized in seven sections with twenty two chapters, covering a wide range of applications. Section I, caters theoretical aspects of FIS in chapter one. Section II, dealing with FIS applications to management related problems and consisting three chapters. Section III, accumulates six chapters to commemorate FIS application to mechanical and industrial engineering problems. Section IV, elaborates FIS application to image processing and cognition problems encompassing four chapters. Section V, describes FIS application to various power system engineering problem in three chapters. Section VI highlights the FIS application to system modeling and control problems and constitutes three chapters. Section VII accommodates two chapters and presents FIS application to civil engineering problem.