DECISION MAKING FOR PRIVATE SCHOOL ESTABLISHMENT USING NEURO-FUZZY METHOD

THAE SU LWIN

M.C.Tech.(THESIS) JANUARY, 2016

DECISION MAKING FOR PRIVATE SCHOOL ESTABLISHMENT USING NEURO-FUZZY METHOD

BY

THAE SU LWIN
B.C.Tech. (Hons:)

Dissertation submitted in partial fulfillment of the

requirements for the degree of

Master of Computer Technology

(M.C.Tech.)

of the

COMPUTER UNIVERSITY, MANDALAY

January, 2016

ACKNOWLEDGEMENTS

First of all, I would like to express my gratitude to **Dr. Win Aye,** Rector, Computer University (Mandalay), for her kind permission to prepare this thesis.

I also would like to offer my special acknowledgement to my supervisor, **Dr. Thi Thi Soe,** Associate Professor, Software Department, Computer University (Mandalay), for her valuable guidance, kind encouragement, and technical assistance suffering to complete my thesis.

I would like to express my grateful thank to all teachers at of Computer University (Mandalay) for their helpful advice and close guidance throughout the period of developing this thesis.

I also would like to give my special thanks to **U Thaung Kyaw**, Associate Professor, Head of English Department, at Computer University (Mandalay) for editing my thesis form the English language point of view.

Besides, I am very grateful to all my teachers, friends and colleagues of Computer University (Mandalay) for their cooperation and help to complete this thesis successfully.

ABSTRACT

Decision Support System of Private education Sector is the process by which an organization uses its resources and capabilities to success or improve an education environment. As a vital activity for companies, new private establishment is also a very risky process. In this thesis, decision-making system for private school establishment is presented 43 attributes of private school requirements. The system applies Neuro-Fuzzy method for deciding private education sector. Neuro-Fuzzy is integrated approach based on fuzzy logic and neural network. This system uses 12 sub-factors and 3 main factors which supports a decision making to establish a new private school in educational sector. In learning phase includes neural networks that learns its internal parameters off-line and fuzzy logic system. The private school establishment system is implemented by using the C# programming language.

TABLE OF CONTENTS

LIST OF EQUATIONS

LIST OF TABLE

CHAPTER 1

INTRODUCTION

1.1 Introduction

Fuzzy logic is based on the central idea that in fuzzy sets each element in the set can assume a value from 0 to 1. Fuzzy sets can be combined to produce meaningful conclusions, and inferences can be made, given a specified fuzzy input function. Neural network techniques aid the fuzzy modeling procedure to learn information about a historical data set, and compute the membership function parameters that best allow the associated FIS to track the given input/output data. ANFIS (adaptive network-based fuzzy inference system) is a class of adaptive networks that is functionally equivalent to FIS. The architecture of ANFIS framework is a feedforward network. The objective is to classify ideas as "good" or "bad", two ANFIS models are built to recognize the corresponding idea status. A processing element of a hybrid neural net is called fuzzy neuron.

The purpose of all education systems is to improve student learning. The quality and equity of student learning depends on many factors. Private schools may belong to one or more associations, School activities, Equipment, Staff and Teacher, Financial, and some other characteristic of the school. Fundamental to the success of the development planning process is the ability of the school to self-evaluate against identified quality indicators.

Other factors that will assist schools in the operation of the planning process include: a growing ability among teachers to use self-evaluation to monitor, evaluate and improve the nature and quality of curricular provision, the enhanced development of staff, which contribute to school effectiveness and improvement; the greater availability of information and data which schools can use to monitor, evaluate and improve the quality of their work; the increased use in schools of information and communication technology hardware, software and support systems, such as classroom management information systems with local and national trends in performance.

1.2 Objectives of the Thesis

This thesis designs and implements a Neuro-Fuzzy logic based private school establishment system to achieve the following objectives:

- To study Neural network and Fuzzy logic
- To realize Neuro-Fuzzy method
- To support the decision-making approach education and business sector
- To decide the most appropriate plan for business areas as education sector

1.3 Motivation

In general, privately managed schools tend to have more autonomy, better resources, better school climate and better performance levels. Private school may be vary in size, level, community type, and student, differences in internal management practices, staff cohesiveness, top-priority goals, and professional climate strategies or ideas to select the best one. Private schools overall have less diverse students, academic excellence, different top priorities, teaching basic literacy skills, private school principals.

1.4 Organization of the Thesis

This thesis is organized as follows. Chapter 1 includes introduction of system, objectives of system and background system. Chapter 2 describes about Neural Network and structure of neural network, fuzzy logic such as fuzzification, membership function, defuzzification, and also different types of Neuro-Fuzzy system, and Adaptive Network-based Fuzzy Inference System (ANFIS). Chapter 3 aims to explain the detailed computation of ANFIS for private school establishment. This explanation includes how to use 12 sub-factors of 3 main factors and how to use rules in computation of consequence parameters of ANFIS. Chapter 4 explains detailed process for to decide private school creation using neural network and fuzzy logic. Also this section includes the processing results with figures. Finally, Chapter 5 presents conclusions, advantages, further extension and limitation.

CHAPTER 2

BACKGROUND THEROY

This chapter is an introduction to neural network and fuzzy set approaches describing the application areas of these approaches.

2.1 Neural Network

Artificial Neural Networks (ANN's) are computational models that are loosely modeled on biological systems and exhibit in a particular way [3]. They are composed by a number of simple processors (neurons) working in parallel, without any centralized control. The neurons are arranged in a particular structure which is usually organized in layers. A system of weighted connections determines the information flow through the network. The behavior of an ANN is determined by the topology of the connections and by the properties of every processing unit, which typically evaluates a mathematical function. The numeric weights of the connections are modified in order to give ANN's a dynamic nature. ANN's possess also adaptive properties, since they are able to modify their output depending on the actual weight. The weight value is dependent on past experience. The learning of an ANN is based on the analysis of input data (training set) and the particular learning algorithms.

The knowledge is eventually embedded into the weight configuration of the network. Neural networks are commonly regarded as learning machines that work on the basis of empirical data. The only means of acquiring knowledge about the world in a connectionist system comes from observational instances. There are no a priori conceptual patterns that could lead to a learning process. The neurons composing the network only perform a very simple task. This consists of evaluating a mathematical function and transmitting a signal. This is similar to the neuronal cells of biological brains. The aim is to adapt to the surrounding data from the system. This rather simplified structure enables ANN's to perform quite complex tasks, endowing connectionist systems with the capability of approximating continuous functions to any required degree of accuracy. The task of a neural network is to realize a mapping of the type: $\varphi : x \in R^n \rightarrow y \in R^m$, (2.1)

where x is a n-dimensional input vector and y is an m-dimensional output vector. ANN's can be variously distinguished in terms of their configurations, topology and learning algorithms. Generally speaking, two main types of con-figurations can be identified: feedforward networks; these possess connections which propagate the information flow in one direction only.

The other type is recurrent networks, whose nodes may have feedback connections, where the input for a neuron may be the output from another neuron. Here the input may be from the particular neuron in question. Each connectionist system is characterized by a particular topology. That is, the organization of its own neurons. The most typical neural architecture is represented by the multilayered network, where the processing units are fully interconnected in three or more layers and the output is interpolated among all the nodes of the network.

2.1.1 Artificial Neural Network

Artificial neural network can be considered as simplified mathematical models of brain-like systems and they function as parallel distributed computing networks. However, in contrast to conventional computers, which are programmed to perform specific task, most neural networks must be taught, or trained. They can learn new associations, new functional dependencies and new patterns.

The study of brain-style computation has its roots over 50 years ago in the work of McCulloch and Pitts [3] and slightly later in Hebb's famous Organization of Behavior [3]. The early work in artificial intelligence was torn between those who believed that intelligent systems could best be built on computers modeled after brains, and those like Minsky and Papert [3] who believed that intelligence was fundamentally symbol processing of the kind readily modeled on the von Neumann computer. For a variety of reasons, the symbol-processing approach became the dominant theme in artificial intelligence. The 1980s showed a rebirth in interest in neural computing: Hopfield [4] provided the mathematical foundation for understanding the dynamics of an important class of networks; Rumelhart and McClell [3] introduced the backpropagation learning algorithm for complex, multi-layer networks and thereby provided an answer to one of the most severe criticisms of the original perceptron work.

Perhaps the most important advantage of neural networks is their adaptively. Neural networks can automatically adjust their weights to optimize their behavior as pattern recognizers, decision makers, system controllers, predictors, etc. Adaptively allows the neural network to perform well even when the environment or the system being controlled varies over time. There are many control problems that can benefit from continual nonlinear modeling and adaptation.

2.1.2 Applications of Neural Network

One of the most popular data-driven techniques attributed by various authors to machine learning, data mining, soft computing etc. is an Artificial Neural Network (ANN). An ANN is an information processing system that roughly replicates the behaviour of a human brain by emulating the operations and connectivity of biological neurons [4].

It performs a human-like reasoning, learns the attitude and stores the relationship of the processes on the basis of a representative data set that already exists. Therefore, generally speaking, the neural networks do not need much of a detailed description or formulation of the underlying process. Depending on the structure of the network, usually a series of connecting neuron *weights* are adjusted in order to fit a series of inputs to another series of known outputs. When the weight of a particular neuron is updated it is said that the neuron is *learning*. The training is the process that neural network learns. Once the training is performed the verification is very fast. Since the connecting weights are not related to some physical identities, the approach is considered as a black-box model. The adaptability, reliability and robustness of an ANN depend upon the source, range, quantity and quality of the data set.

2.1.3 Type of Neural Network

Structure of an ANN can be classified into three groups by arrangement of neurons and the connection patterns of the layers: feedforward (error backpropagation networks), feedback (recurrent neural networks and adaptive resonance memories), self-organizing (Kohonen networks). Also neural networks can be roughly categorized into two types in terms of their learning features: *supervised* learning algorithms, where networks learn to fit known inputs to known outputs, and *unsupervised* learning algorithms, where no desired output to a set of input is defined. The classification is not unique and different research groups make different classifications. One of the possible classifications is shown in Figure 2.1.

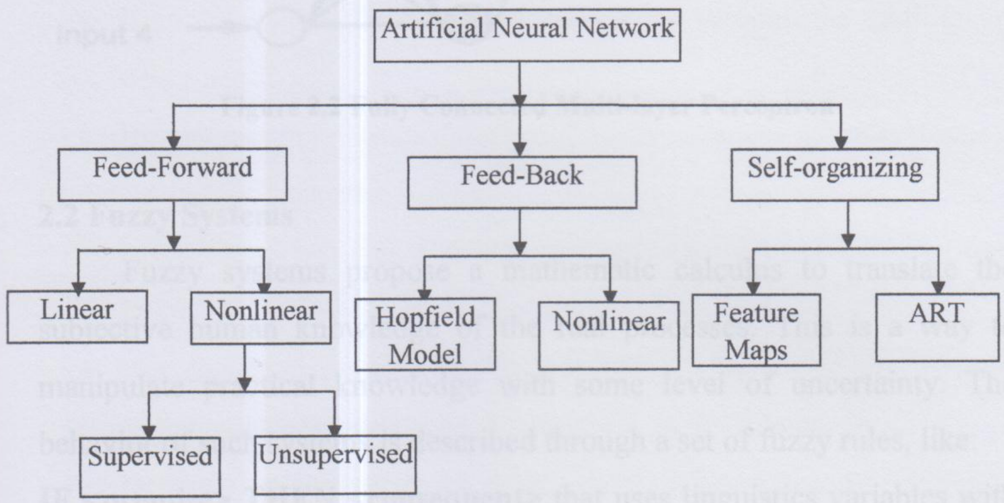


Figure 2.1 Classification of Neural Network

The feedforward neural networks consist of three or more layers of nodes: one input layer, one output layer and one or more hidden layers. The input vector x passed to the network is directly passed to the node activation output of input layer without any computation. One or more hidden layers of nodes between input and output layer provide additional computations. Then the output layer generates the mapping output vector z. Each of the hidden and output layer has a set of connections, with a corresponding strength-weight, between itself and each node of preceding layer. Such structure of a network is called a *Multi-Layer Perceptron* (MLP). Figure 2.2 shows a typical multi-layer perceptron.

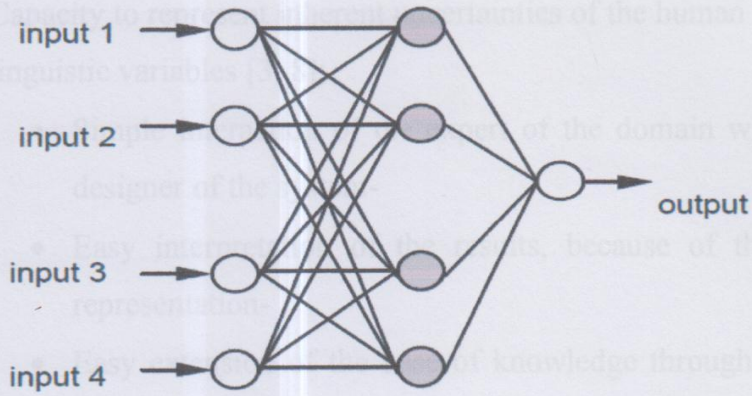


Figure 2.2 Fully Connected Multi-layer Perceptron

2.2 Fuzzy Systems

Fuzzy systems propose a mathematic calculus to translate the subjective human knowledge of the real processes. This is a way to manipulate practical knowledge with some level of uncertainty. The behavior of such systems is described through a set of fuzzy rules, like: **IF <premise> THEN <consequent>** that uses linguistics variables with symbolic terms.

Each term represents a fuzzy set. The terms of the input space (typically 5-7 for each linguistic variable) compose the fuzzy partition. The fuzzy inference mechanism consists of three stages: in the first stage, the values of the numerical inputs are mapped by a function according to a degree of compatibility of the respective fuzzy sets; this operation can be called fuzzyfication. In the second stage, the fuzzy system processes the rules in accordance with the firing strengths of the inputs. In the third stage, the resultant fuzzy values are transformed again into numerical values; this operation can be called defuzzyfication. Essentially, this procedure makes possible the use fuzzy categories in representation of words and abstracts ideas of the human beings in the description of the decision-taking procedure. The advantages of the fuzzy systems are:

Capacity to represent inherent uncertainties of the human knowledge with linguistic variables [3, 8];

- Simple interaction of the expert of the domain with the engineer designer of the system-
- Easy interpretation of the results, because of the natural rules representation-
- Easy extension of the base of knowledge through the addition of new rules-
- Robustness in relation of the possible disturbances in the system.

And its disadvantages are:

- Incapable to generalize, or either, it only answers to what is written in its rule base-
- Not robust in relation to the topological changes of the system, such changes would demand alterations in the rule base-
- Depends on the existence of a expert to determine the inference logical rules-

2.2.1 Basic Component of Fuzzy System

Fuzzy logic systems commonly contain expert IF-THEN rules and can be characterized in terms of their fundamental constituents: fuzzification, rule base, inference, defuzzification. Figure 2.3 is a schematic representation of such a fuzzy system. Fuzzification is a mapping from a crisp input space to fuzzy sets in a defined universe:

$$U : x_i \in R \rightarrow X \in U \subset R^q. \qquad (2.2)$$

Here x_i represents a crisp value and q is the number of fuzzy classes.

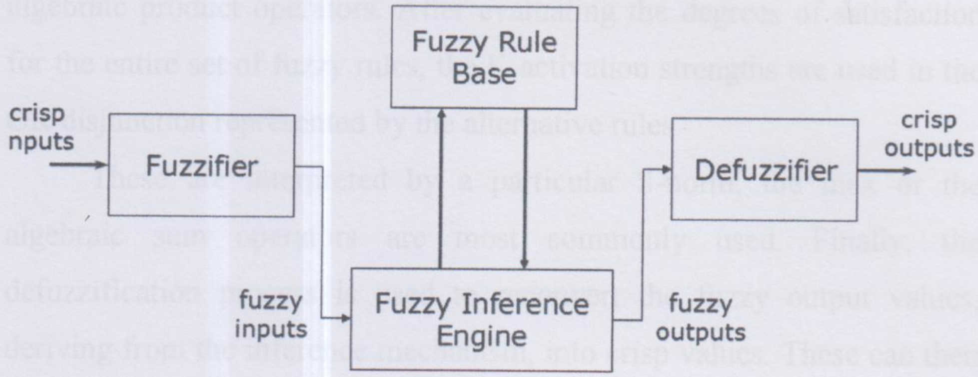


Figure 2.3 Basic Components of Fuzzy System

The fuzzy sets are characterized by membership functions which portray the degree of belonging of xi to the values in U, $\mu F(x_i) : U \rightarrow [0, 1]$. The rule base is constituted by an ensemble of fuzzy rules and the knowledge is expressed in the following form:

IF x_1 is A_1^k AND. . .AND x_n is A_n^k THEN y_1 is A_i^k AND. . .AND y_m is b_m^k, (2.3)

where the index k = 1, . . . ,K indicates the k-th rule among the K rules in the rule base; A_1^k and b_j^k are fuzzy sets. These are defined over the input components xi, i = 1, . . . , n, and the output components y_j , j = 1, . . . ,m, respectively. The rule is a fuzzy implication that is usually represented by a Cartesian product of the membership functions of antecedents and consequents.

The fuzzy inference process can be described by starting with the definition of the membership functions $\mu_{ik}(\cdot)$ related to the kth fuzzy rule and evaluated for each input component of a sample vector $x = (x_1, . . . , x_n)$. The most commonly employed membership functions are the triangular and the Gaussian functions. The values obtained by the fuzzification contribute to the AND conjunction of each rule, which is interpreted by a particular T-norm. This is most commonly the min or the algebraic product operators. After evaluating the degrees of satisfaction for the entire set of fuzzy rules, the K activation strengths are used in the OR disjunction represented by the alternative rules.

These are interpreted by a particular S-norm, the max or the algebraic sum operators are most commonly used. Finally, the defuzzification process is used to reconvert the fuzzy output values, deriving from the inference mechanism, into crisp values. These can then be eventually employed in different contexts. The most common strategy for defuzzification is to use the center of area method which gives the center of gravity of the output membership function.

2.2.2 Fuzzy Sets

Fuzzy techniques in the form of approximate reasoning provide decision support and expert systems with powerful reasoning capabilities. The permissiveness of fuzziness in the human thought process suggests that much of the logic behind thought processing is not traditional two valued logic or even multivalued logic, but logic with fuzzy truths, fuzzy connectedness, and fuzzy rules of inference. A fuzzy set is an extension of a crisp set. Crisp sets allow only full membership or no membership at all, whereas fuzzy sets allow partial membership. In a crisp set, membership or non-membership of element x in set A is described by a characteristic function , where and . Fuzzy set theory extends this concept by defining partial membership. A fuzzy set A on a universe of discourse U is characterized by a membership function that takes values in the interval . Fuzzy sets represent commonsense linguistic labels like *slow, fast, small, large, heavy, low, medium, high, tall,* etc. A given element can be a member of more than one fuzzy set at a time. A fuzzy set A in U may be represented as a set of ordered pairs [3,9].

2.2.3 Membership Functions

Various types of membership functions are used, including triangular, trapezoidal, generalized bell shaped, Gaussian curves, polynomial curves, and sigmoid functions. The membership function maps each element of X to a membership value between 0 and 1. Several basic functions are:

- piece-wise linear functions
- the Gaussian distribution function
- the sigmoid curve
- quadratic and cubic polynomial curves

The simplest membership functions are formed using straight lines. In Figure 2.5, the simplest is the *triangular* membership function, and it has the function name trimf . This function is nothing more than a collection of three points forming a triangle. In Figure 2.6, the *trapezoidal* membership function, trapmf, has a flat top and really is just a truncated triangle curve. These straight line membership functions have the advantage of simplicity.

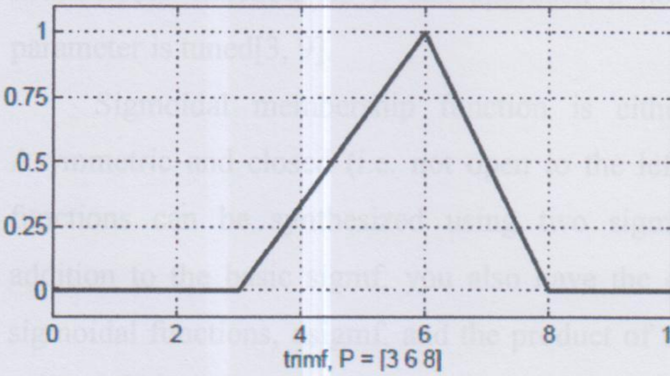


Figure 2.4.Triangular Membership Function

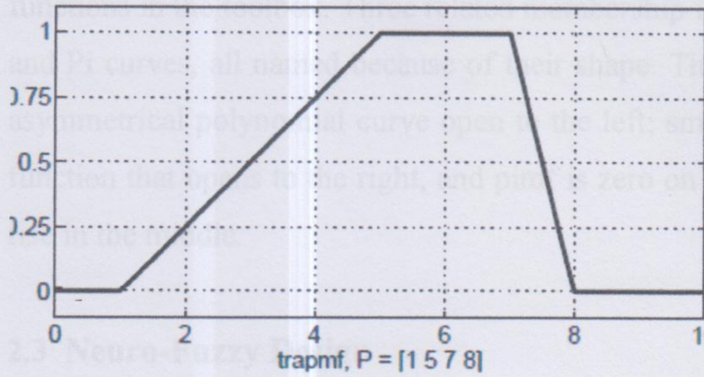


Figure 2.5.Trapezoidal Membership Function

A *trapezoidal* membership function is a piecewise linear, continuous function, controlled by four parameters {a, b, c, d}

$$\mu_{trapezoid}(x; a, b, c, d) = \left\{ \begin{array}{ll} 0 & , x \leq a \\ \frac{x-a}{b-a} & , a \leq x \leq b \\ 1 & , b \leq x \leq c \\ \frac{d-x}{d-c} & , c \leq x \leq d \\ 0 & , d \leq x \end{array} \right\}, x \in \mathbb{R}$$

Two membership functions are built on the *Gaussian* distribution curve: a simple Gaussian curve and a two-sided composite of two different Gaussian curves. The *generalized bell* membership function is specified by three parameters and has the function name gbellmf. The bell membership function has one more parameter than the Gaussian membership function, so it can approach a non-fuzzy set if the free parameter is tuned[3, 9].

Sigmoidal membership function is either open left or right. Asymmetric and closed (i.e. not open to the left or right) membership functions can be synthesized using two sigmoidal functions, so in addition to the basic sigmf, you also have the difference between two sigmoidal functions, dsigmf, and the product of two sigmoidal functions psigmf. Polynomial-based curves account for several of the membership functions in the toolbox. Three related membership functions are the Z, S, and Pi curves, all named because of their shape. The function zmf is the asymmetrical polynomial curve open to the left; smf is the mirror-image function that opens to the right, and pimf is zero on both extremes with a rise in the middle.

2.3 Neuro-Fuzzy Design

The Artificial Neural Networks (ANNS) have been very successful in recognizing nonlinear patterns from noisy, high frequency data and have been very useful forecasting tools. However, there has been criticism of their inability to transparently explain how a decision (forecast) is reached. Also, unlike fuzzy logic it is impossible to incorporate *a priori* information about the problem into the ANN system. Fuzzy logic can quantify vague information and produce transparent decision-making logic. The drawbacks of fuzzy logic are the lack of a learning capability and the necessity for an expert knowledge about the system.

Neural fuzzy inference systems introduce a parallel architecture and learning capability to a fuzzy inference system. Each fuzzy rule is created using the ANN and it is a data driven process. Fuzzy neural networks embed fuzzy logic into the ANN by fuzzifying the learning algorithms. This system uses a neuro-fuzzy combination where the ANN is used for identification (forecasting) and FLC extracts the decision from the ANN's output.

Finding a trading rule with FLC should not be confused with training of an ANN. An ANN uses a learning algorithm to map input variables (e.g. lagged interest rate, lagged order flow) into output variables (e.g. exchange rate change). In other words, an ANN is a nonlinear and dynamic system that learns from known input-output combinations. ANNs have been shown to have very good forecasting ability, but lack explanatory capability. By contrast, FLCs have no training capability and the mapping between inputs and output is generated from expert knowledge in the form of "if-then" rules. That is why it would be ideal to combine ANNs and FLCs to create a so-called neuro-fuzzy (NF) technology [1].

2.3.1 Introduction of Fuzzy Logic

Fuzzy sets were introduced by Zadeh [3] as a means of representing and manipulating data that was not precise, but rather fuzzy. There is a strong relationship between Boolean logic and the concept of a subset, there is a similar strong relationship between fuzzy logic and fuzzy subset theory. In classical set theory, a subset A of a set X can be defined by its characteristic function X_A as a mapping from the elements of X to the elements of the set {0, 1},

$$X_A: X \rightarrow \{0, 1\}.$$

This mapping may be represented as a set of ordered pairs, with exactly one ordered pair present for each element of X. The first element of the ordered pair is an element of the set X, and the second element is an element of the set {0, 1}. The value zero is used to represent non-membership, and the value one is used to represent membership. The truth or falsity of the statement "x is in A" which is determined by the ordered pair (x, !A(x)). The statement is true if the second element of the ordered pair is 1, and the statement is false if it is 0.

Similarly, a fuzzy subset A of a set X can be defined as a set of ordered pairs, each with the first element from X, and the second element from the interval [0, 1], with exactly one ordered pair present for each element of X. This defines a mapping, μA, between elements of the set X and values in the interval [0, 1]. The value zero is used to represent complete nonmembership; the value one is used to represent complete membership, and values in between are used to represent intermediate degrees of membership.

The set X is referred to as the universe of discourse for the fuzzy subset A. Frequently, the mapping μA is described as a function, the membership function of A. The degree to which the statement "x is in A" is true is determined by finding the ordered pair (x, μA(x)). The degree of truth of the statement is the second element of the ordered pair. It should be noted that the terms membership function and fuzzy subset get used interchangeably.

2.4 Neural Fuzzy Systems

While fuzzy logic performs an inference mechanism under cognitive uncertainty, computational neural networks offer exciting advantages, such as learning, adaptation, fault-tolerance, parallelism and generalization. Neural networks are used to tune membership functions of fuzzy systems that are employed as decision-making systems for controlling equipment. Although fuzzy logic can encode expert knowledge directly using rules with linguistic labels, it usually takes a lot of time to design and tune the membership functions which quantitatively define these linquistic labels. Neural network learning techniques can automate this process and substantially reduce development time and cost while improving performance [4].

In theory, neural networks and fuzzy systems are equivalent in that they are convertible, yet in practice each has its own advantages and disadvantages. For neural networks, the knowledge is automatically acquired by the backpropagation algorithm, but the learning process is relatively slow and analysis of the trained network is difficult (black box). Neither is it possible to extract structural knowledge (rules) from the trained neural network, nor can we integrate special information about the problem into the neural network in order to simplify the learning procedure.

Fuzzy systems are more favorable in that their behavior can be explained based on fuzzy rules and thus their performance can be adjusted by tuning the rules. But since, in general, knowledge acquisition is difficult and also the universe of discourse of each input variable needs to be divided into several intervals, applications of fuzzy systems are restricted to the fields where expert knowledge is available and the number of input variables is small.

To overcome the problem of knowledge acquisition, neural networks are extended to automatically extract fuzzy rules from numerical data. Cooperative approaches use neural networks to optimize certain parameters of an ordinary fuzzy system, or to preprocess data and extract fuzzy (control) rules from data. The basic processing elements of neural networks are called artificial neurons, or simply neurons. The signal flow form of neuron inputs, x_j , is considered to be unidirectional as indicated by arrows, as is a neuron's output signal flow. All signals and weights are real numbers. The input neurons do not change the input signals so their output is the same as their input. The signal xi interacts with the weight w_i to produce the product $p_i = w_i x_i$, $i = 1, \dots, n$. The input information pi is aggregated, by addition, to produce the input net = $p_1 + \cdots + p_n = w_1 x_1 + \cdots + w_n x_n$ to the neuron. The neuron uses its transfer function f, which could be a sigmoidal function, f(t) = 11 + e−t to compute the output y = f(net) = f(w1x1 + · · · + wnxn).

This simple neural net, which employs multiplication, addition, and sigmoidal f, will be called as regular (or standard) neural net.

2.5 Neuro-Fuzzy Engineering

The basic idea behind the neuro-fuzzy engineering approach is to pass the spatial information through a series of steps:

1. Convert real-valued spatial data into a fuzzified representation of the same information.
2. Train the fuzzified spatial information with a three-layer multilayer perceptron neural network. The output of the neural network is taken to be a fuzzy representation of the desired output.
3. The output of the neural network in step 2 is then de-fuzzified to produce individual real values of the desired output [7].

After the neural network in step 2 is trained to satisfaction, it is analyzed in order to extract fuzzy rules that can be used in association with the defined fuzzy membership functions used in steps 1 and 3.

2.5.1 Fuzzy Neural Networks Architecture

A fuzzy neural network seeks to blend the elements of these fuzzy and neural network computations into single connectionist architecture. There are several fuzzy neural network architectures [5, 8, 9]. The model of FuNN consists of five layers: input variable layer, condition elements (input fuzzy membership function) layer, rule layer, action elements (output fuzzy member function) layer, and output variables layer.

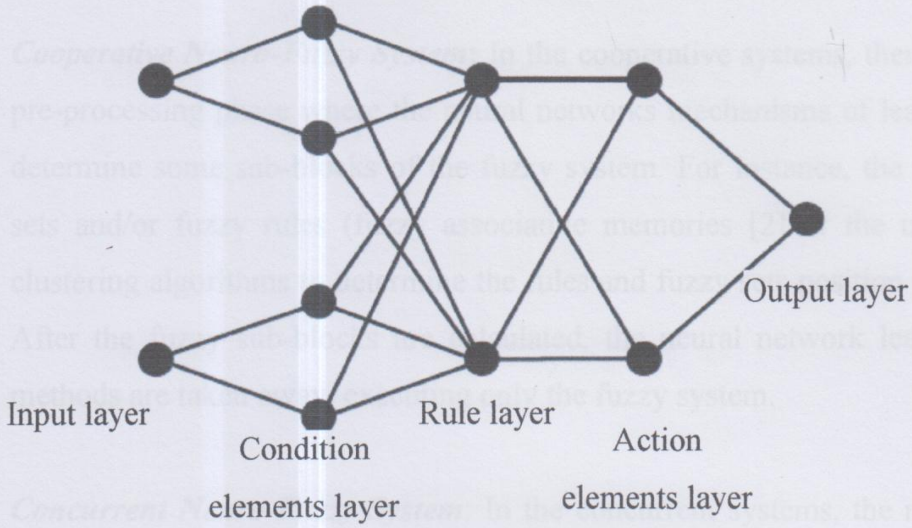


Figure 2.6.Fuzzy Neural Network (FuNN) Architecture

These elements are shown schematically in Figure 2.6. A bias node can also be included in this architecture but is not shown in the figure. Ordinarily, we employ triangular membership functions for the second and fourth layers. In the simplified scheme shown in Figure 2.8, each of the two inputs can be fuzzified in the condition layer by showing the degree of their membership in a fuzzy set (such as the degree to which they are HIGH or LOW). The number of fuzzy values need not be the same for the various inputs. Thus, one input could be connected to two condition layer nodes, and another input could be connected to four condition layer nodes.

2.6 Types of Neuro-Fuzzy Systems

In general, all the combinations of techniques based on neural networks and fuzzy logic can be called neuro-fuzzy systems. The different combinations of these techniques can be divided, in accordance with [10], in the following classes:

***Cooperative Neuro-Fuzzy System*:** In the cooperative systems, there is a pre-processing phase where the neural networks mechanisms of learning determine some sub-blocks of the fuzzy system. For instance, the fuzzy sets and/or fuzzy rules (fuzzy associative memories [2] or the use of clustering algorithms to determine the rules and fuzzy sets position [10]). After the fuzzy sub-blocks are calculated, the neural network learning methods are taken away, executing only the fuzzy system.

***Concurrent Neuro-Fuzzy System*:** In the concurrent systems, the neural network and the fuzzy system work continuously together. In general, the neural networks pre-processes the inputs (or pos-processes the outputs) of the fuzzy system [2, 10].

***Hybrid Neuro-Fuzzy System*:** In this category, a neural network is used to learn some parameters of the fuzzy system (parameters of the fuzzy sets, fuzzy rules and weights of the rules) of a fuzzy system in an iterative way. The majority of the researchers uses the neuro-fuzzy term to refer only hybrid neuro-fuzzy system [2, 10].

2.6.1 Cooperative Neuro-Fuzzy Systems

In a cooperative system, the neural networks are only used in an initial phase [2, 10]. In this case, the neural networks determine sub-blocks of the fuzzy system using training data. After this, the neural networks are removed and only the fuzzy system is executed. In the cooperative neuro-fuzzy systems, the structure is not total interpretable what can be considered a disadvantage in Figure 2.7.

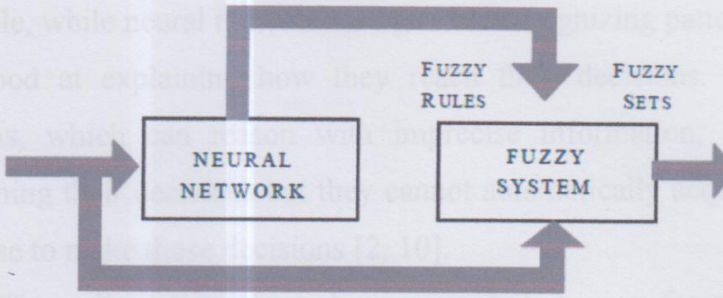


Figure 2.7.Cooperative Systems

2.6.2 Concurrent Neuro-Fuzzy Systems

A concurrent system is not a neuro-fuzzy system in the strict sense, because the neural network works together with the fuzzy system. This means that the inputs entered in the fuzzy system are pre-processed and then the neural network processes the outputs of the concurrent system or in the reverse way. In the concurrent neuro-fuzzy systems, the results are not completely interpretable, what can be considered a disadvantage in Figure 2.8 [2, 10].

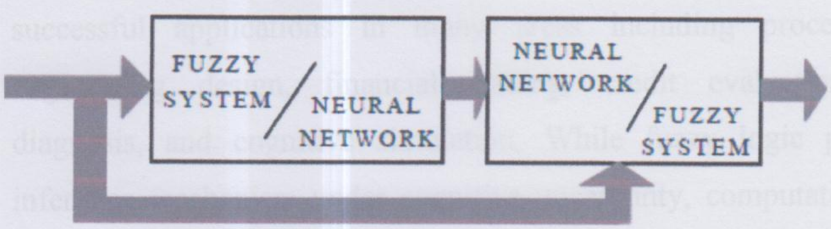


Figure 2.8.Concurrent Systems

2.7 Hybrid Systems

Hybrid systems combining fuzzy logic, neural networks, genetic algorithms, and expert systems are proving their effectiveness in a wide variety of real-world problems. Every intelligent technique has particular computational properties (e.g. ability to learn, explanation of decisions) that make them suited for particular problems and not for others. For example, while neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions but they cannot automatically acquire the rules they use to make those decisions [2, 10].

These limitations have been a central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of individual techniques. Hybrid systems are also important when considering the varied nature of application domains. Many complex domains have many different component problems, each of which may require different types of processing. If there is a complex application which has two distinct sub-problems, say a signal processing task and a serial reasoning task, then a neural network and an expert system respectively can be used for solving these separate tasks.

The use of intelligent hybrid systems is growing rapidly with successful applications in many areas including process control, engineering design, financial trading, credit evaluation, medical diagnosis, and cognitive simulation. While fuzzy logic provides an inference mechanism under cognitive uncertainty, computational neural networks offer exciting advantages, such as learning, adaptation, fault tolerance, parallelism and generalization. To enable a system to deal with cognitive uncertainties in a manner more like humans, one may incorporate the concept of fuzzy logic into the neural networks. The resulting *hybrid system* is called fuzzy neural, neural fuzzy, neuro-fuzzy or fuzzy-neuro network.

2.7.1 Model of Fuzzy Neural Systems

Two possible models of fuzzy neural systems are:

1. In response to linguistic statements, the fuzzy interface block provides an input vector to a multi-layer neural network. The neural network can be adapted (trained) to yield desired command outputs or decisions [8] shown in Figure 2.9.

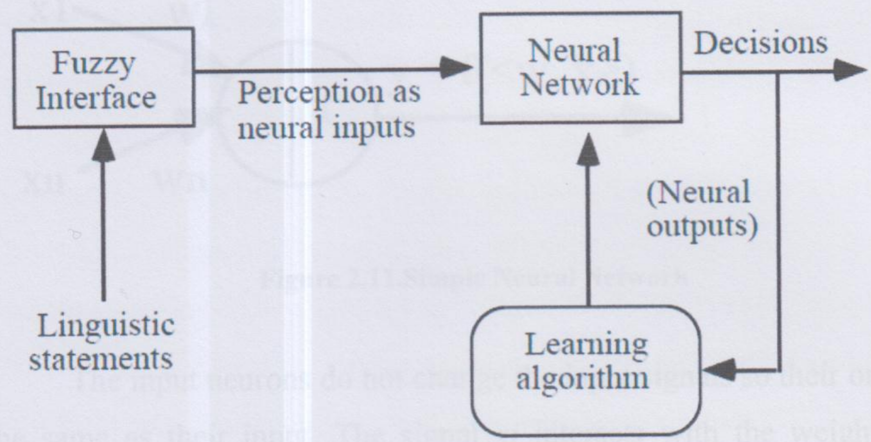


Figure 2.9.First Model of Fuzzy Neural System

2. A multi-layered neural network drives the fuzzy inference mechanism shown in Figure 2.10.

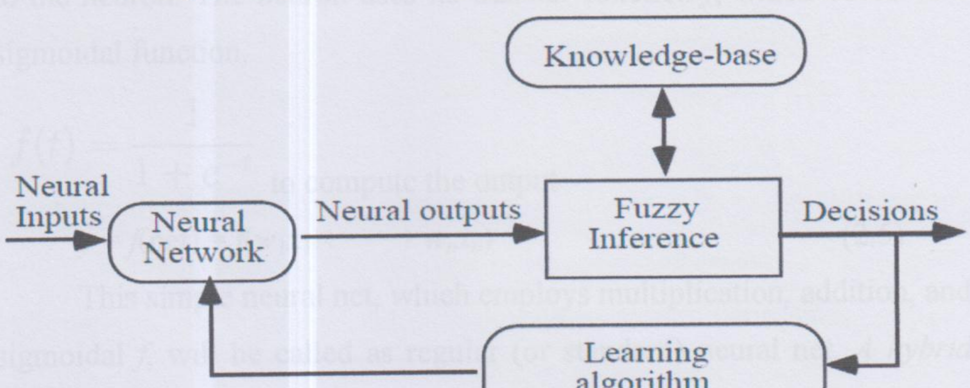


Figure 2.10.Second Model of Fuzzy Neural System

The basic processing elements of neural networks are called *artificial neurons*, or simply *neurons*. The signal flow form of neuron inputs, *xj*, is considered to be unidirectionals indicated by arrows, as is a neuron's output signal flow. In Figure 2.11, all signals and weights are real numbers.

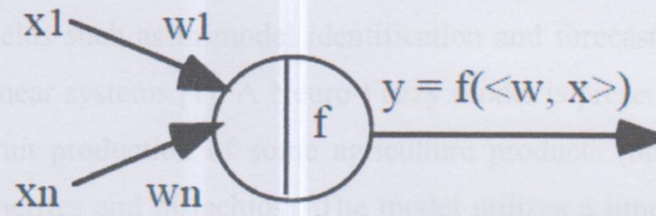


Figure 2.11.Simple Neural Network

The input neurons do not change the input signals so their output is the same as their input. The signal *xi* interacts with the weight w_i to produce the product $pi = w_i x_i,\ i = 1, \ldots, n$. The input information p_i is aggregated, by addition, to produce the input

$$net = p_1 + \cdots + p_n = w_1 x_1 + \cdots + w_n x_n, \tag{2.4}$$

to the neuron. The neuron uses its transfer function *f*, which could be a sigmoidal function,

$f(t) = \dfrac{1}{1 + e^{-t}}$ to compute the output

$$y = f(\text{net}) = f(w_1 x_1 + \cdots + w_n x_n) \tag{2.5}$$

This simple neural net, which employs multiplication, addition, and sigmoidal *f*, will be called as regular (or standard) neural net. *A hybrid neural net* is a neural net with crisp signals and weights and crisp transfer function. However, (i) we can combine x_i and w_i using some other continuous operation; (ii) we can aggregate the *pi*'s with some other continuous function; (iii) f can be any continuous function from input to output. We emphasize here that all inputs, outputs and the weights of a hybrid neural net are real numbers taken from the unit interval [0, 1].

A processing element of a hybrid neural net is called *fuzzy neuron*.

2.8 Related Works

Neuro-fuzzy techniques are finding a practical application in many fields such as in model identification and forecasting of linear and non-linear systems [1]. A Neuro-Fuzzy model is presented for forecasting the fruit production of some agriculture products (olives, lemons, oranges, cherries and pistachios). The model utilizes a time series of yearly data. The fruit forecasting is based on Adaptive Neural Fuzzy Inference System (ANFIS). ANFIS uses a combination of the least-squares method and the backprobagation gradient descent method to estimate the optimal food forecast parameters for each year. The results are compared to those of an Autoregressive (AR) model and an Autoregressive Moving Average model (ARMA).

A Neuro-Fuzzy modeling technique was used to predict the effective of thermal conductivity of various fruits and vegetables. A total of 676 data point was used to develop the neuro-fuzzy model considering the inputs as the fraction of water content, temperature and apparent porosity of food materials. The complexity of the data set which incorporates wide ranges of temperature (including those below freezing points) made it difficult for the data to be predicted by normal analytical and conventional models. However, the adaptive neuro-fuzzy model (ANFIS) was able to predict conductivity values which closely matched the experimental values by providing lowest mean square error compared to multivariable regression and conventional artificial neural network

(ANN) models. This method also alleviates the problem of determining the hidden structure of the neural network layer by trial and error[5].

T.Kavitha, M.Chandra Sekhar, and CNV Sridhar [9] proposed a neuro fuzzy rule-based approach to generate models relating car seat design variables to affective user satisfaction. Affective user satisfaction such as body contact, sweat and heat generation, shoulder support, head rest support, lumbar support and child safety were modeled for Car seat designs. The main objective is to generate a new car seat model in order to provide maximum human comfort. Maximum human comfort is estimated by an intelligence system called Neuro fuzzy system, where it gives the comfort of seat with respect to its influencing parameters. By adopting this Neuro-Fuzzy logic eliminated the antiquity of modifications, whether they are correct or not and the results give us an accurate decision to adopt the change or not [9].

One benefit of fuzzy systems [3] is that the rule base can be created from expert knowledge, used to specify fuzzy sets to partition all variables and a sufficient number of fuzzy rules to describe the input/output relation of the problem at hand. However, a fuzzy system that is constructed by expert knowledge alone will usually not perform as required when it is applied because the expert can be wrong about the location of the fuzzy sets and the number of rules. A manual tuning process must usually be appended to the design stage which results in modifying the membership functions and/or the rule base of the fuzzy system. This tuning process can be very time-consuming and error-prone. Also, in many applications expert knowledge is only partially available or not at all. It is therefore useful to support the definition of the fuzzy rule base by automatic learning approaches that make use of available data samples. This is possible since, once the components of the fuzzy system is put in a parametric form, the fuzzy inference system becomes a parametric model which can be tuned by a learning procedure.

Fuzzy logic and artificial neural networks are complementary technologies in the design of intelligent systems. The combination of these two technologies into an integrated system appears to be a promising path toward the development of Intelligent Systems capable of capturing qualities characterizing the human brain. Both neural networks and fuzzy logic are powerful design techniques that have their strengths and weaknesses. The integrated system will have the advantages of both neural networks (e.g. learning abilities, optimization abilities and connectionist structures) and fuzzy systems (humanlike IF-THEN rules thinking and ease of incorporating expert knowledge) [2].

CHAPTER 3

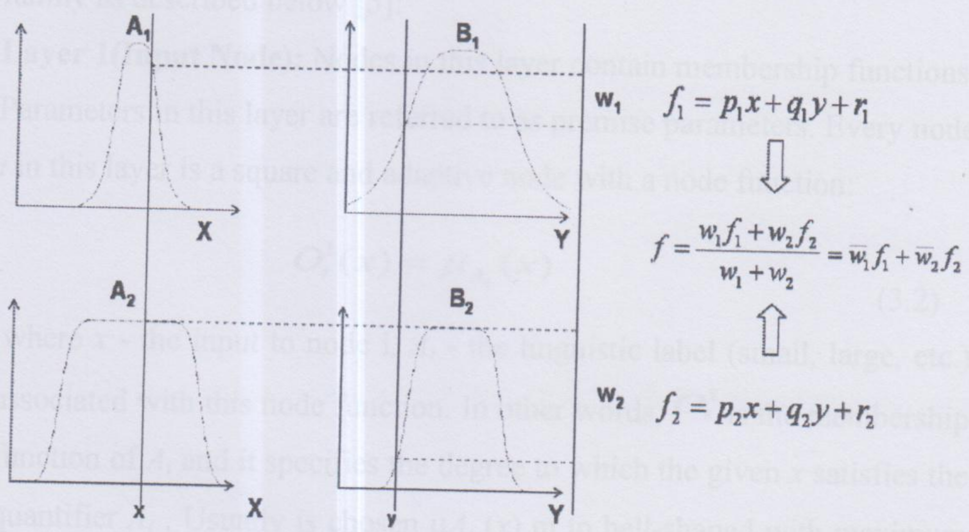
ADAPTIVE NEURAL FUZZY INFERENCE SYSTEM

This chapter explains the detail process of ANFIS which is used for deciding the private school establishment. It involves 3 main factors and 12 sub-factors.

3.1 Adaptive Neural Fuzzy Inference System

A Neuro-Fuzzy system is defined as a combination of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) in such a way that neural network learning algorithm is used to determine the parameters of FIS [5]. Adaptive Neural Fuzzy Inference System (ANFIS) is a system that belongs to Neuro-Fuzzy category.

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feedforward type. Due to this minimal restriction, the adaptive network's applications are immediate and immense in various areas.



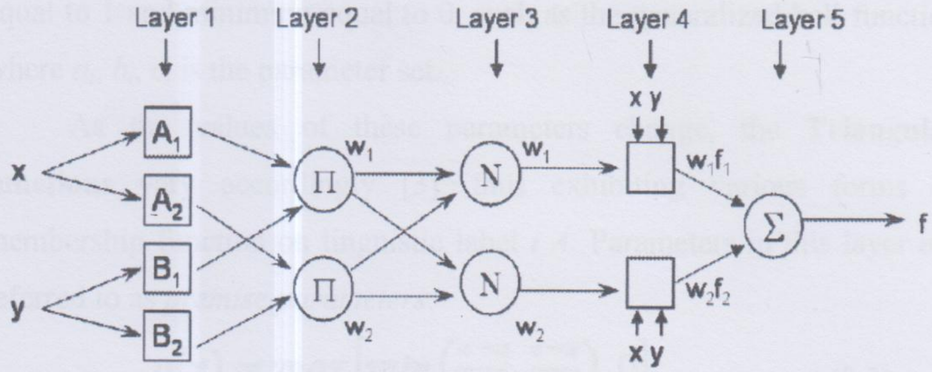


Figure 3.1 ANFIS Architecture

For simplicity, is assumed the fuzzy inference system under consideration has two inputs x and y , and one output f. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugenos' type:

Rule1: If x is A_1 and y is B_1 then $f_1 = p_1 \times x + q_1 \times y + r_1$

Rule2: If x is A_2 and y is B_2 then $f_2 = p_2 \times x + q_2 \times y + r_2$ (3.1)

The ANFIS architecture and the reasoning mechanism is depicted in Figure 3.1.

3.2 Node Functions in the Layer

The node functions in the same layer are of the same function family as described below [5]:

Layer 1(Input Node): Nodes in this layer contain membership functions. Parameters in this layer are referred to as premise parameters. Every node i in this layer is a square and adaptive node with a node function:

$$O_i^1(x) = \mu_{A_i}(x) \tag{3.2}$$

where x - the input to node i, A_i - the linguistic label (small, large, etc.) associated with this node function. In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i . Usually is chosen μA_i (x) m to bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function where a_i, b_i, c_i is the parameter set.

As the values of these parameters change, the **Triangular functions** vary accordingly [3], thus exhibiting various forms of membership function on linguistic label *i A*. Parameters in this layer are referred to as *premise parameters*.

$$\mu(x) = max\left[min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right] \quad (3.3)$$

Layer 2 (Rule nodes): Every node in this layer is a circle node labeled π, which multiplies the incoming signal and sends the product out.

Every node in this layer is a circle node labeled II, whose output represents a firing strength of a rule. This layer chooses the minimum value of two input weights. In this layer, the AND/OR operator is applied to get one output that represents the results of the antecedent for a fuzzy rule, that is, firing strength. It means the degrees by which the antecedent part of the rule is satisfied and it indicates the shape of the output function for that rule. The node generates the output (firing strength) by cross multiplying all the incoming signals:

$$O_{2.i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), \quad i = 1, 2. \quad (3.4)$$

Layer 3 (Average nodes): Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rules firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2., \quad (3.5)$$

For convenience, output of this layer will be called *normalized firing strengths*.

Consequent nodes (Layer 4): Every node i in this layer is a square node with a node function where: $\overline{w}_i$ the output of layer 3{ p_i , q_i , r_i } - the parameter set. Parameters in this layer will be referred to as *consequent parameters* in Figure 3.2.

$$O_i^4(x) = \overline{w}_i \cdot f_i = \overline{w}_i(p_1 \cdot x + q_i \cdot y + r_i) \tag{3.6}$$

Output node (Layer 5): The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals, i.e.

$$O_i^5(x) = overalloutput \qquad O_i^5(x) = \sum_i \overline{w}_i \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \tag{3.7}$$

3.3 Parametric Identification

Two types of parameters characterize a fuzzy model: those determining the shape and distribution of the input fuzzy sets and those describing the output fuzzy sets (or linear models). Many Neuro-Fuzzy systems use direct nonlinear optimization to identify all the parameters of a fuzzy system [7]. A very large number of Neuro-Fuzzy systems are based on backpropagation. The general idea of such heuristics is to slightly modify the membership functions of a fuzzy rule according to how much the rule contributes to the overall output of the fuzzy system.

From the proposed type-3 ANFIS architecture (see Figure. 3.1), it is observed that given the values of premise parameters, the overall output can be expressed as a linear combinations of the consequent parameters. More precisely, the output f in Figure 3.1 can be rewritten as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \overline{w}_1 f_1 + \overline{w}_2 f_2$$
$$= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2 \qquad (3.8)$$

which is linear in the consequent parameters (p_l, q_1, r_l, p_2, q_2 and r_2). Therefore, the hybrid learning algorithm can be applied directly.

3.4 Structural Identification

Before fuzzy rule parameters can be optimized, the structure of the fuzzy rule base must be defined. This involves determining the number of rules and the granularity of the data space, i.e. the number of fuzzy sets used to partition each variable. In fuzzy rule-based systems, as in any other modeling technique, there is a tradeoff between accuracy and complexity. The more rules, the finer the approximation of the nonlinear mapping can be obtained by the fuzzy system, but also more parameters have to be estimated, thus the cost and complexity increase. A possible approach to structure identification is to perform a stepwise search through the fuzzy model space. Once again, these search strategies fall into one of two general categories: forward selection and backward elimination. [7]

- Forward selection: Starting from a very simple rule base, new fuzzy rules are dynamically added or the density of fuzzy sets is incrementally increased.
- Backward elimination: An initial fuzzy rule base, constructed from a priori knowledge or by learning from data, is reduced, until a minimum of the error function is found.

3.5 Triangular Membership Function

A *triangular* membership function is piecewise linear, and derived from the trapezoidal membership function by merging the two shoulder points into one, that is, setting b = c. Smooth, differentiable versions of the trapezoidal and triangular membership functions can be obtained by replacing the linear segments corresponding to the intervals $a \leq x \leq b$ [3]. Triangular curves depend on three parameters *a, b,* and *c* and are given by

$$f(x;a,b,c) = \begin{cases} 0 & \text{for } x < a \\ \dfrac{x-a}{b-a} & \text{for } a \leq x < b \\ \dfrac{c-x}{c-b} & \text{for } b \leq x \leq c \\ 0 & \text{for } x > c \end{cases} \tag{3.9}$$

3.6 Consequent Parameters Calculations for ANFIS

In this system, input variables are applied of four types of linguistics values in membership function.

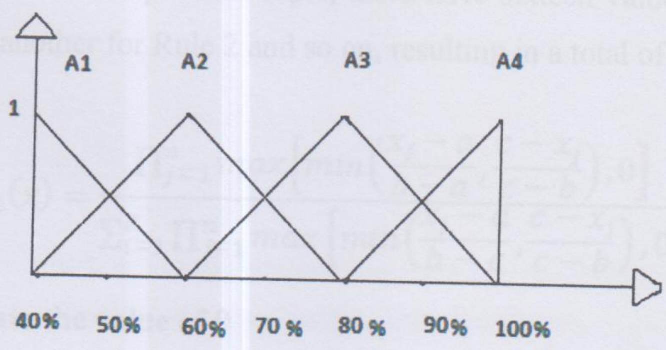


Figure 3.2 Consequent Parameters Calculations

There are sixteen rules for output decision-making process.

Rule 1: If x is A1 and y is A1 then output is 40.

Rule 2: If x is A1 and y is A2 then output is 40.

Rule 3: If x is A1 and y is A3 then output is 50.

Rule 4: If x is A1 and y is A4 then output is 50.

Rule 5: If x is A2 and y is A1 then output is 40.

Rule 6: If x is A2 and y is A2 then output is 60.

Rule 7: If x is A2 and y is A3 then output is 70.

Rule 8: If x is A2 and y is A4 then output is 70.

Rule 9: If x is A3 and y is A1 then output is 50.

Rule 10: If x is A3 and y is A2 then output is 70.

Rule 11: If x is A3 and y is A3 then output is 80.

Rule 12: If x is A3 and y is A4 then output is 90.

Rule 13: If x is A4 and y is A1 then output is 50.

Rule 14: If x is A4 and y is A2 then output is 70.

Rule 15: If x is A4 and y is A3 then output is 90.

Rule 16: If x is A4 and y is A4 then output is 100.

Least Square Estimate

For each input data-tuple, there have sixteen values of **ξ**, one for Rule 1, another for Rule 2 and so on, resulting in a total of 256 values.

$$\xi_i(x) = \frac{\prod_{j=1}^{n} max\left[min\left(\frac{x_j - a}{b - a}, \frac{c - x_j}{c - b}\right), 0\right]}{\sum_{i=1}^{R} \prod_{j=1}^{n} max\left[min\left(\frac{x_j - a}{b - c}, \frac{c - x_j}{c - b}\right), 0\right]} \qquad (3.10)$$

Calculate the value of θ

With **ξ**(x) completely specified the transpose of **ξ**(x) is determined and placed into a matrix Φ.

$$\emptyset = \begin{bmatrix} \xi^T(x^1) \\ \vdots \\ \xi^T(x^{16}) \end{bmatrix} \tag{3.11}$$

And the desire outputs placed in matrix Y.

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_{16} \end{bmatrix} \tag{3.12}$$

Calculate the value of θ using Y and Φ.

$$\theta = (\emptyset^T \emptyset)^{-1} \emptyset^T Y \tag{3.13}$$

Calculate the output function

Calculate the output for the input data set.

$$f(x|\theta) = \theta \xi(x) \tag{3.14}$$

3.7 Attributes for Requirements of Private School

In Table 3.1, there are 43 attributes of 12 sub-factors in 3 main factors. These attributes are taken from **Sar Pann Aein** private school and **Aung Pann Tai** private school in Pyin Oo Lwin.

Table 3.1. Main factors, sub-factors and attributes of the system

Main factors	Sub-factors	Attributes
School Activity	Teaching achievement	No of student, No of teacher and No of study guide
	Health	Clinic, Medical care, School clean and Water supply
	Advertising	No of newspaper, No of journal, Television and No of billboard
	Social activity	Religion festivities, School sport and Competition of essay writing, drawing and debate
Equipment	Campus	Area, Soccer, Tennis court and Basketball court
	Environment	Market, Noisy place, City, Cyber game and Cinema
	Buildings and rooms	No of student in one room, Classroom width and Theatre
	Multi-media rooms	Laboratory , Computer aided instruction room, Audio lab, Library and Student used
Staff and Teacher, Finance	Experience for teacher	Service, Well-trained and Qualification
	Experience for staff and guide	Service, Well-trained and Qualification
	Income	No of student, No of scholar student and Loss money
	Outcome	Charity, Salary andTax

The calculation of each attributrs in 12 sub factors for private school establishment system are shown in the following tables.Table 3.2 is shown the calculation of attributes for Teaching achievement sub factor.

Table 3.2. Calculation of Attributes for Teaching achievement

Number of teacher /Number of student	Percentage	Number of study guide / Number of student	Percentage
1/20	50%	1/8	50%

In Table 3.3 to Table 3.11, there are shown the values of attributes for specific sub factor.

Table 3.3.Calculation of Attributes for Health

Clinic		Medical care		School clean				Water supply		
Yes	No	weekly	monthly	everyday	2 day	weekly	monthly	spring	well	Purified water
25%	0%	20%	10%	25%	20%	10%	5%	10%	20%	30%

Table 3.4.Calculation of Attributes for Advertising

Number of newspaper		Number of journals		Television		Number of billboards	
Number	%	Number	%	Yes	No	Number	%
1	5%	2	8%			10	10%
2	10%	5	15%	25%	0%	15	15%
3	20%	7	20%			20	20%
4	25%	10	25%			30	30%

Table 3.5.Calculation of Attributes for Social Activity

Religious festival		School sport		Competition of essay, writing, drawing and debate	
Festival	%	sports	%	number	%
Thadingyut	5%	Football	5%	1	10%
Thasaungdain	5%	Tennis	5%	2	20%
Christmas	5%	Basketball	5%	3	30%
Muslim religious holiday	5%	Badminton	5%	4	40%
Chinese new year	5%	Running event	5%	5	50%

Table 3.6.Calculation of Attributes for Campus

Area		Soccer		Tennis court		Basketball court	
		Yes	No	Yes	No	Yes	No
400*400	40%	20%	0%	20%	0%	20%	0%

Table 3.7.Calculation of Attributes for Environment

Market		Noisy place		City		Cyber game		Cinema	
Near	Not near	Near	Not near	In downtown	Not downtown	Near	Not near	Near	Not near
0%	20%	0%	20%	0%	20%	0%	20%	0%	20%

Table 3.8.Calculation of Attributes for Buildings and Rooms

Number of students in one room / classroom wide	percentages	Theatre	
		Yes	No
1/18	60%	20%	0%

Table 3.9.Calculation of attributes for Multi-Media Rooms

Laboratory		Computer aided instruction		Audio lab		Library		Student used	
Yes	No	Yes	No	Yes	No	Yes	No	Used	%
20%	0%	15%	0%	20%	0%	20%	0%	20%	5%
								60%	15%
								100%	25%

Table 3.10.Calculation of Attributes for Experience for Teacher

Service		Well-trained		Qualification		
		Yes	No	Bachelor	Master	Ph.D.
No service	0%					
1 year	2%					
.	.	10%	0%	10%	20%	30%
.	.					
.	.					
30years	30%					

Table 3.11.Calculation of Attributes for Experience for Staff and Guide

Service		Well-trained		Qualification			
		Yes	No	Certificate of matric exam	Bachelor	Master	L.C.C.I
No service	0%						
1 year	2%						
.	.	10%	0%	10%	20%	30%	10%
.	.						
.	.						
20years	40%						

In Table 3.12 and 3.13, user must enter these attributes to calculate the percentages of sub-factors.

Table 3.12.Calculation of Attributes for Income

(number of student /number of scholar student)*100	Loss money
Scholar percentages	Entry percentages

Table 3.13 Attributes Calculation for Outcome

Charity	Salary	Tax
Entry percentages	Entry percentages	Entry percentages

3.7.1 Case Study

There are four sub-factors in School Activities: Teaching Achievement, Health, Advertising and Social Activity. In Teaching achievement, the input for Number of student is **2000**, Number of teacher is **100** and Number of study guide is **150** in sub-factor of Teaching Achievement. The total percentage of this factor is **80%.** In Health, the input for Clinic is **Yes**, Medical care is **Monthly**, school clean is **Every day** and water supply is **well**. The total percentage of this factor is **80%.** Other attributes of all sub-factors must be input and click *Show %* button to display the percentages of specific factors.

After entry of four 12 factors of main factors, the system calculates total percentage to calculate fuzzy number by using Trigular Membership Function. This is started for first layer fuzzification process using every two input parameters.

In layer 1 for learning phase, the initial input of x=80% and y=80% is calculating membership function by using Equation 3.4. For example,

For A1 of input x, a=40, b=60, c=80

$$\mu(x) = max\left[min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right]$$

$$\mu(80) = max\left[min\left(\frac{80-40}{40-40},\frac{60-80}{60-40}\right),0\right] = 0$$

For A1 of input y, a=40, b=60, c=80

$$\mu(y) = max\left[min\left(\frac{y-a}{b-a},\frac{c-y}{c-b}\right),0\right]$$

$$\mu(80) = max\left[min\left(\frac{80-40}{60-40},\frac{80-80}{80-40}\right),0\right] = 0$$

…

$\mu_{A1}(x) = 0,$ $\quad$ $\mu_{A2}(x) = 0,$

$\mu_{A3}(x) = 1,$ $\quad$ $\mu_{A4}(x) = 0,$

$\mu_{A1}(y) = 0,$ $\quad$ $\mu_{A2}(y) = 0,$

$\mu_{A3}(y) = 1,$ $\quad$ $\mu_{A4}(y) = 0,$

In layer 2, weight values are calculated by using Equation 3.5.

$\omega_1 = \mu_{A1}(x)\mu_{A1}(y) = 0$ $\quad$ $\omega_2 = \mu_{A1}(x)\mu_{A2}(y) = 0$

$\omega_3 = \mu_{A1}(x)\mu_{A3}(y) = 0$ $\quad$ $\omega_4 = \mu_{A1}(x)\mu_{A4}(y) = 0$

$\omega_5 = \mu_{A2}(x)\mu_{A1}(y) = 0$ $\quad$ $\omega_6 = \mu_{A2}(x)\mu_{A2}(y) = 0$

$\omega_7 = \mu_{A2}(x)\mu_{A3}(y) = 0$ $\quad$ $\omega_8 = \mu_{A2}(x)\mu_{A4}(y) = 0$

$\omega_9 = \mu_{A3}(x)\mu_{A1}(y) = 0$ $\quad$ $\omega_{10} = \mu_{A3}(x)\mu_{A2}(y) = 0$

$\omega_{11} = \mu_{A3}(x)\mu_{A3}(y) = 1$ $\quad$ $\omega_{12} = \mu_{A3}(x)\mu_{A4}(y) = 0$

$\omega_{13} = \mu_{A4}(x)\mu_{A1}(y) = 0$ $\quad$ $\omega_{14} = \mu_{A4}(x)\mu_{A2}(y) = 0$

$\omega_{15} = \mu_{A4}(x)\mu_{A3}(y) = 0$ $\quad$ $\omega_{16} = \mu_{A4}(x)\mu_{A4}(y) = 0$

In layer 3, strong weight calculated by using Equation 3.6. For example,

$$\overline{\omega_1} = \frac{\omega_1}{\omega_1 + \omega_2 + \omega_3 + \omega_4 + \cdots + \omega_{13} + \omega_{14} + \omega_{15} + \omega_{16}} = 0$$

$$\overline{\omega_2} = \frac{\omega_2}{\omega_1 + \omega_2 + \omega_3 + \omega_4 + \cdots + \omega_{13} + \omega_{14} + \omega_{15} + \omega_{16}} = 0$$

…

In layer 4, there is calculation for output node using Equation 3.7.

$\overline{\omega_1}f_1 = 0$ $\quad$ $\overline{\omega_2}f_2 = 0$ $\quad$ $\overline{\omega_3}f_3 = 0$ $\quad$ $\overline{\omega_4}f_4 = 0$ $\quad$ $\overline{\omega_5}f_5 = 0$ $\quad$ $\overline{\omega_6}f_6 = 0$

$\overline{\omega_7}f_7 = 0$ $\quad$ $\overline{\omega_8}f_8 = 0$ $\quad$ $\overline{\omega_9}f_9 = 0$ $\quad$ $\overline{\omega_{10}}f_{10} = 0$ $\quad$ $\overline{\omega_{11}}f_{11} = 1 * 80 = 80$

$\overline{\omega_{12}}f_{12} = 0$ $\quad$ $\overline{\omega_{13}}f_{13} = 0$ $\quad$ $\overline{\omega_{14}}f_{14} = 0$ $\overline{\omega_{15}}f_{15} = 0$ $\quad$ $\overline{\omega_{16}}f_{16} = 0$

In layer 5, there is calculation final output for first input by using Equation 3.8.

Output= $\overline{\omega_1}f_1 + \overline{\omega_2}f_2 + \overline{\omega_3}f_3 + \overline{\omega_4}f_4 - \overline{\omega_5}f_5 + \overline{\omega_6}f_6 + \overline{\omega_7}f_7 + \overline{\omega_8}f_8 + \overline{\omega_9}f_9 + \overline{\omega_{10}}f_{10} + \overline{\omega_{11}}f_{11} + \overline{\omega_{12}}f_{12} + \overline{\omega_{13}}f_{13} + \overline{\omega_{14}}f_{14} + \overline{\omega_{15}}f_{15} + \overline{\omega_{16}}f_{16} = 80$

This output is used in secondary input to calculate the final output in layer 5 through layer 1, 2, 3 and 4. These processes are continued until inputs are not combination. Finally, the system outputs the result of the decision "success" or "impossible".

CHAPTER 4

SYSTEM DESIGN AND IMPLEMENTATION

This chapter presents design and implementation of the decision making system for private school establishment that is based on Neuro-Fuzzy approach.

4.1 Overview of the System

Initializing the Neural Network with Input variables and Output variables, for simulation of neural network with private school influencing parameters, it is directed to fuzzy inference system. New private school establishing system deploys its attributes like the influencing parameters which are School activities, Equipment, Staff and Teacher, Finance, for main attributes sub-attributes are teaching achievement, health, advertising and social activities, in school activities. Campus, Environment, Building and Rooms, and Multimedia Rooms are sub-attributes in Equipment. Experiences for teacher, Experience for Staff and Guide, Income and Outcome are sub-attributes of Staff and Teacher, Finance. Artificial Neural Network and its respective parameters like Hidden layer, Train and Simulate options is initiated. In the part of this, neural network is trained, based on the input parameters. After training the artificial neural network model, the trained network is simulated to obtain the overall output based on input attributes. So, in this connection, different simulation data sets are used to predict the simulation output i.e. overall output for private school level. In Figure 4.1, input factors are 12 sub-factors and these factors are processed in ANFIS. Then the system produces the decision result for private school.

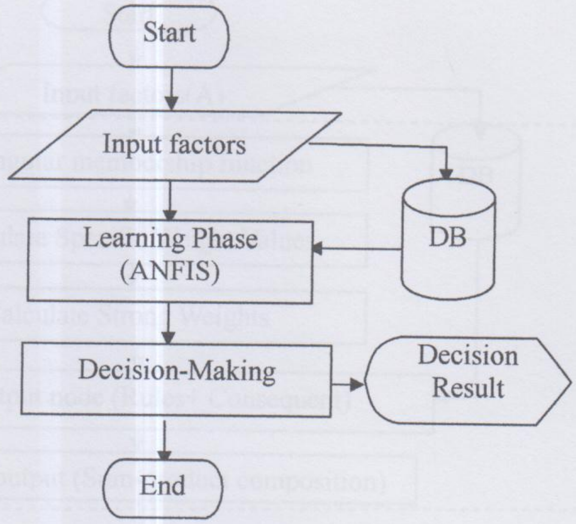


Figure 4.1 Overview of the System Design

4.1.1 System Flow Diagram

In Figure 4.2, Neural Network is initialized with input of 12 sub-factors of three main factors and one output variable for new private school establishment system.

- Neural Network is trained by using triangular membership function to convert linguistic variable to fuzzy variables.
- Simulation of Network is processed with different data sets, to obtain best results.
- Fuzzy Inference System is created with respective input and its membership functions.
- Output of Neural Network is integrated with Fuzzy Inference system using equation 3.11.

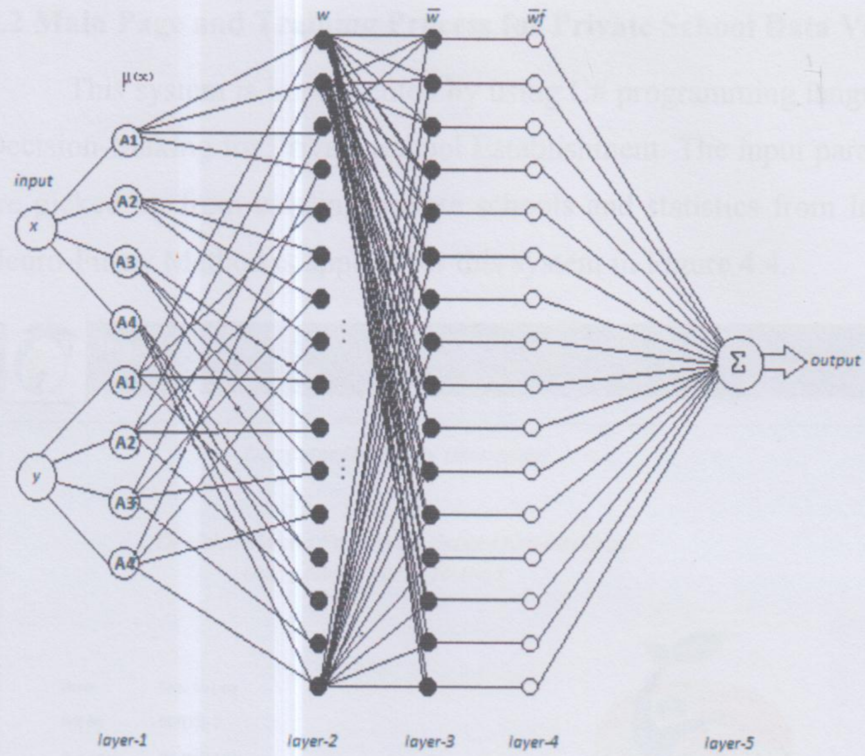


Figure 4.3 Training Methodology of System using ANFIS

Input MFs were linked by all possible combinations of if-and-then rules defining an output constant for each rule. The presented training methodology of ANFIS system is shown in Figure 4.3. The modeling process starts by obtaining a data set (input-output data pairs) and dividing it into training and checking data sets. Training data constitutes a set of input and output vectors. The data is normalized in order to make it suitable for the training process. This normalized data was utilized as the inputs and outputs to train the ANFIS.

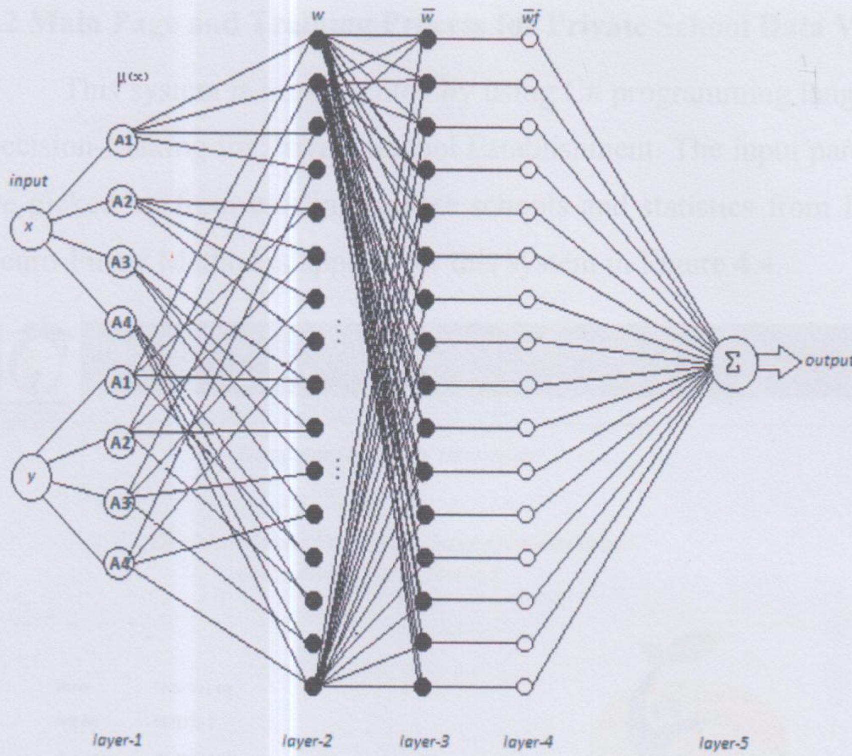


Figure 4.3 Training Methodology of System using ANFIS

Input MFs were linked by all possible combinations of if-and-then rules defining an output constant for each rule. The presented training methodology of ANFIS system is shown in Figure 4.3. The modeling process starts by obtaining a data set (input-output data pairs) and dividing it into training and checking data sets. Training data constitutes a set of input and output vectors. The data is normalized in order to make it suitable for the training process. This normalized data was utilized as the inputs and outputs to train the ANFIS.

4.2 Main Page and Training Process for Private School Data Values

This system is implemented by using C# programming language of Decision-Making for Private School Establishment. The input parameters are picked up from existing private schools and statistics from Internet. Neuro-Fuzzy Method is applied for this system in Figure 4.4.

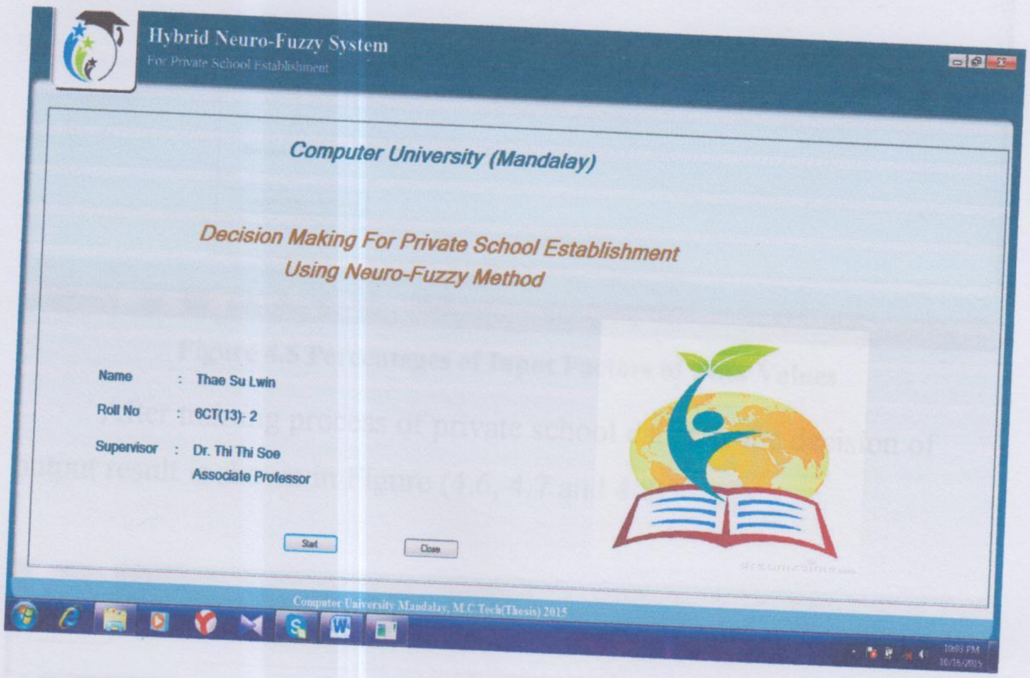


Figure 4.4 Main Page

In Figure 4.5, there are 12 sub-factors of three main factors. The left side of the window displays maximum, medium and minimum values which values are used in 12 sub-factors. This window displays training process for maximum values of private schooll requirements data sets.

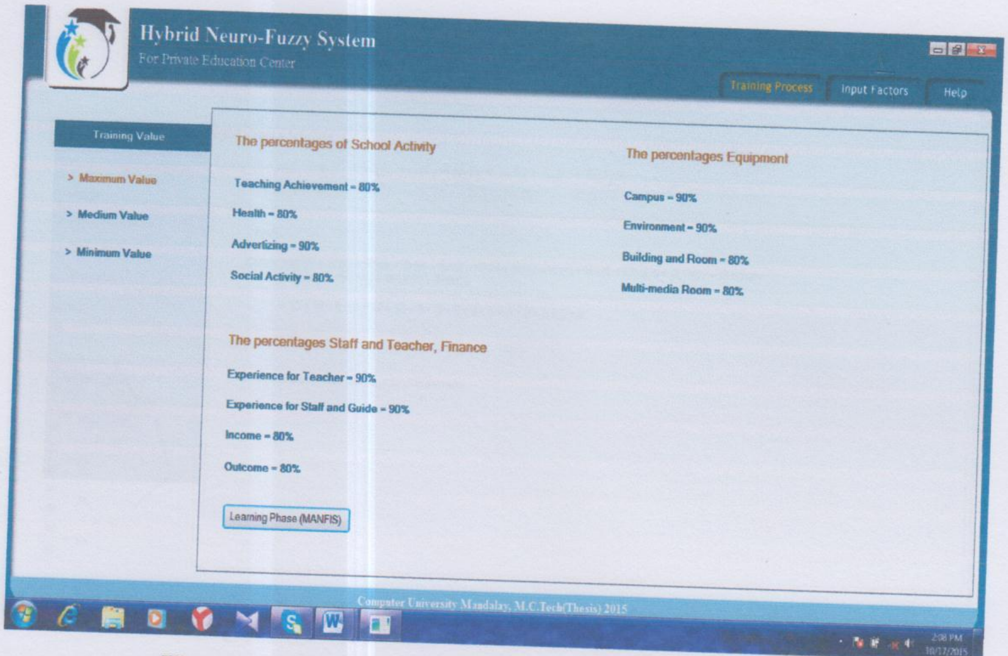


Figure 4.5 Percentages of Input Factors of Data Values

After training process of private school data set, the decision of output result is shown in Figure (4.6, 4.7 and 4.8).

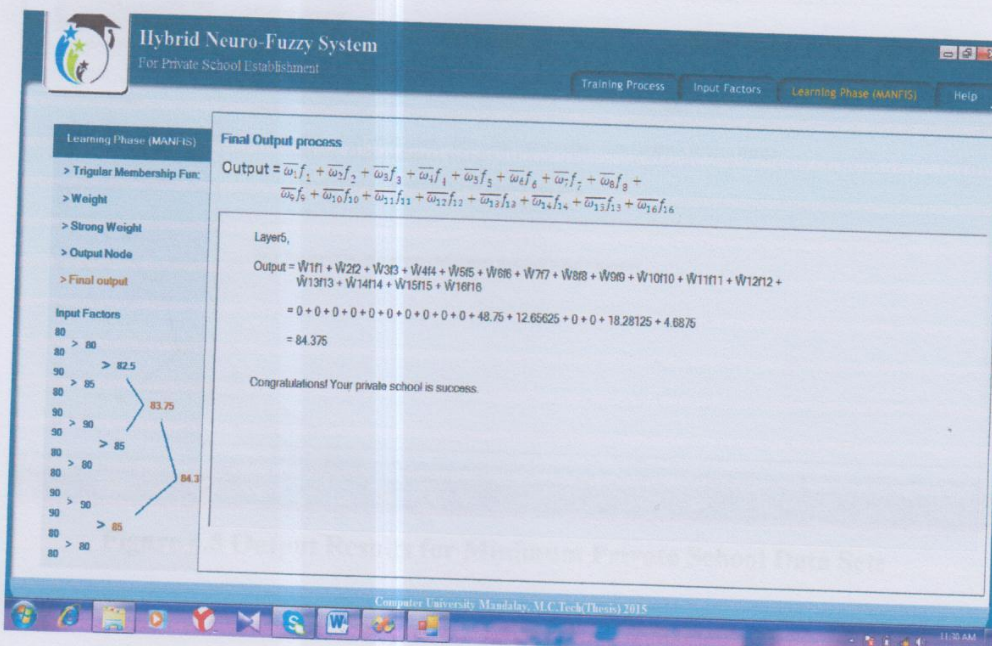


Figure 4.6 Output Results for Maximum Data Sets

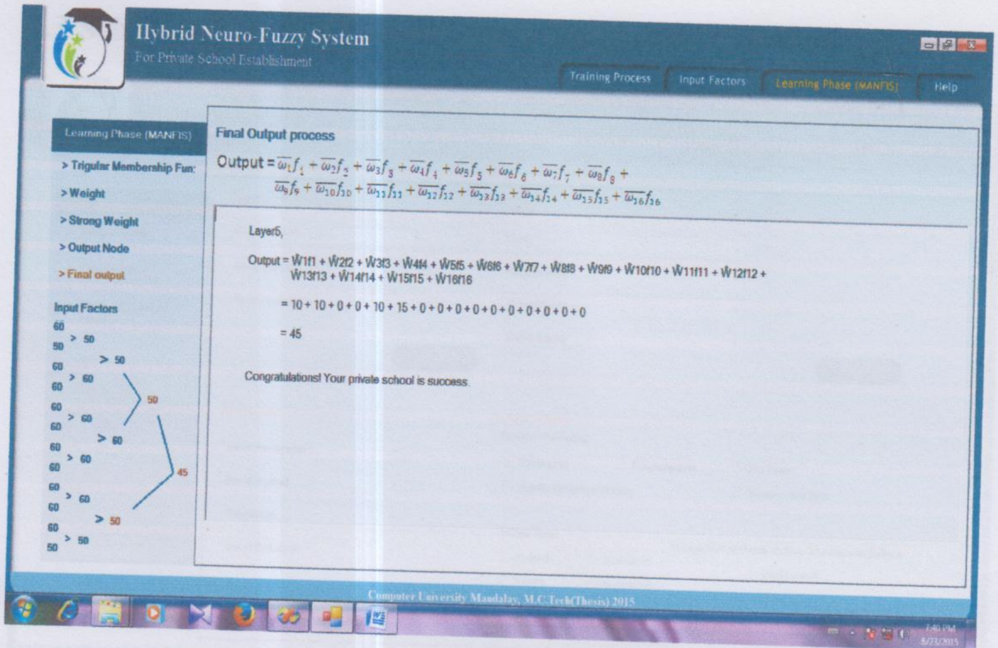


Figure 4.7 Output Results for Private School Data Sets

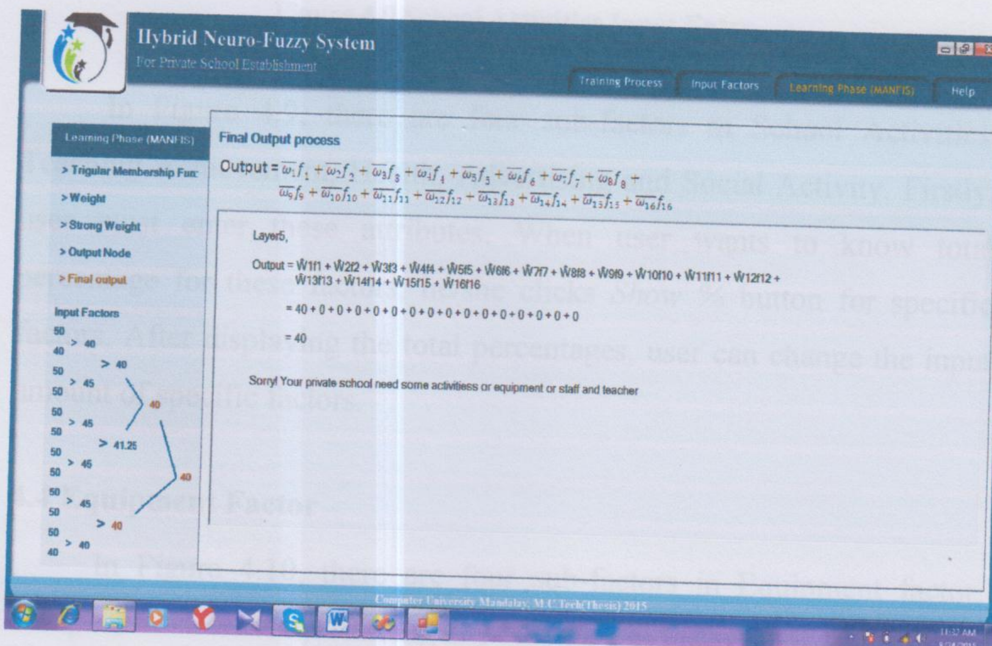


Figure 4.8 Output Results for Minimum Private School Data Sets

4.3 School Activities

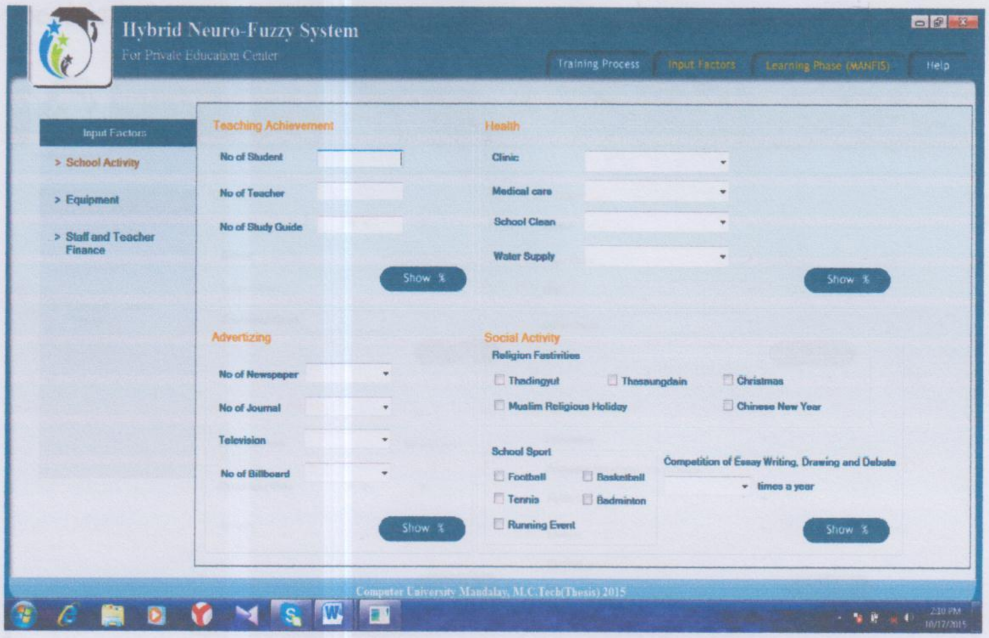


Figure 4.9 School Activities Input Entry

In Figure 4.9, there are four sub-factors in School Activities: Teaching Achievement, Health, Advertising and Social Activity. Firstly, user must enter these attributes. When user wants to know total percentage for these factors, he/she clicks *Show %* button for specific factors. After displaying the total percentages, user can change the input amount of specific factors.

4.4 Equipment Factor

In Figure 4.10, there are four sub-factors in Equipment factor: Campus, Environment, Building and Rooms and Multimedia Room. User also must enter these attributes. When user wants to know total percentage for these factors, he/she clicks *Show %* button for specific factors. After displaying the total percentages, user can change the input amount of specific factors. Some of the factors can be chosen from specific values.

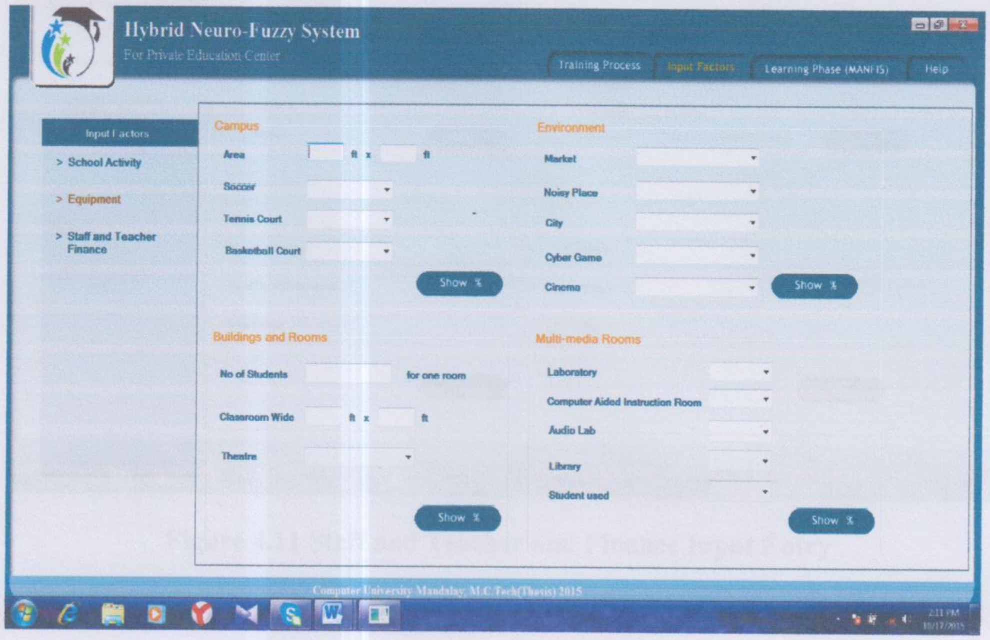


Figure 4.10 Equipment Input Entry

4.5 Staff, Teacher and Finance

Figure 4.11 includes four sub-factors in Staff and Teacher and Finance factor: Experience for Teacher, Experience for Staff and Guides, Income and Outcome. User also must enter these attributes. When user wants to know total percentage for these factors, he/she clicks *Show %* button for specific factors. After displaying the total percentages, user can change the input amount of specific factors. Qualification factors can be chosen for Teachers, Staff and Guides.

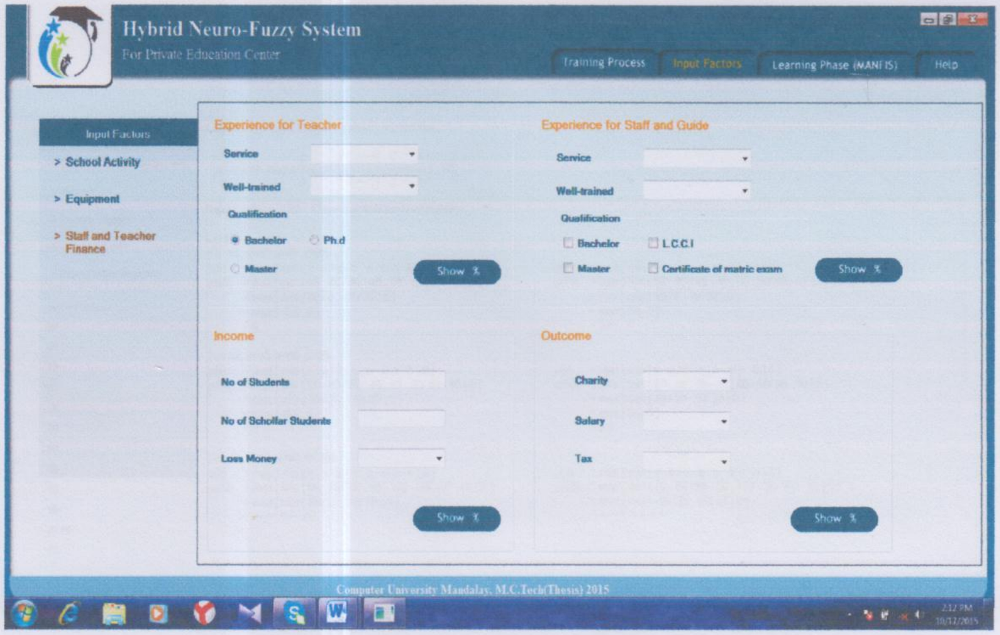


Figure 4.11 Staff and Teacher and Finance Input Entry

4.6 Triangular Membership Function

After entry 12 sub-factors of 3 main factors, the system calculates total percentage to calculate fuzzy number by using Triangular Membership Function in Figure 4.12. This is started for first layer fuzzification process using every two input parameters.

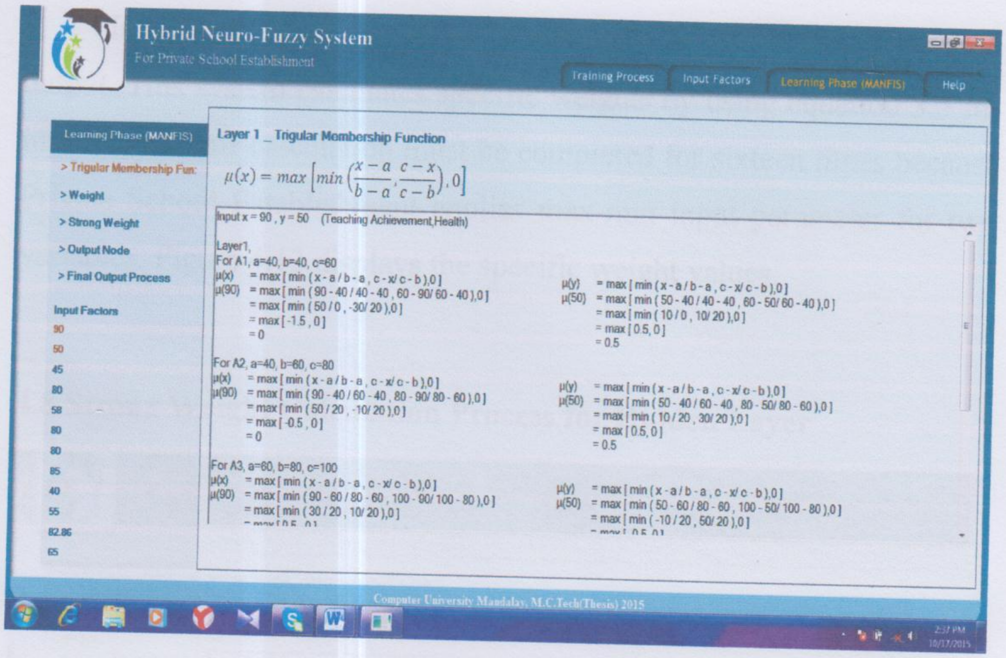


Figure 4.12 Membership Function Calculation

4.7 Weight Calculation Process for Layer 2

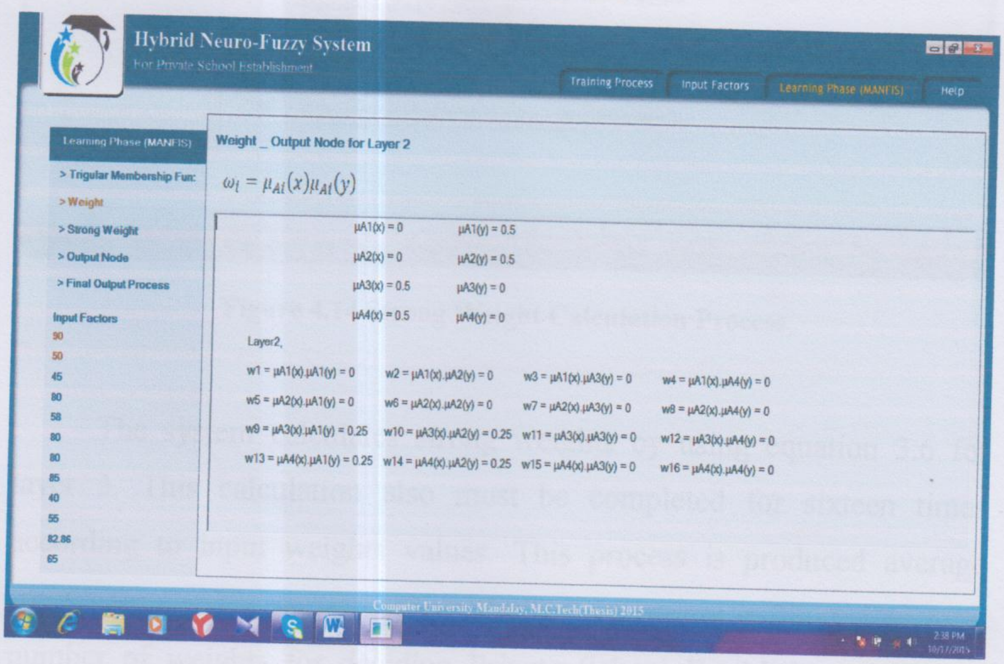


Figure 4.13 Weight Calculation Process for Layer 2

In ANFIS, there are assign weights for specific layer to produce net output. This system calculates specific weights by using equation 3.5 for input layer. This calculation must be completed for sixteen times because Private School Establishment applies max-min input parameter for two variables. Figure 4.13 displays the specific weight values.

4.8 Strong Weight Calculation Process for Hidden Layer

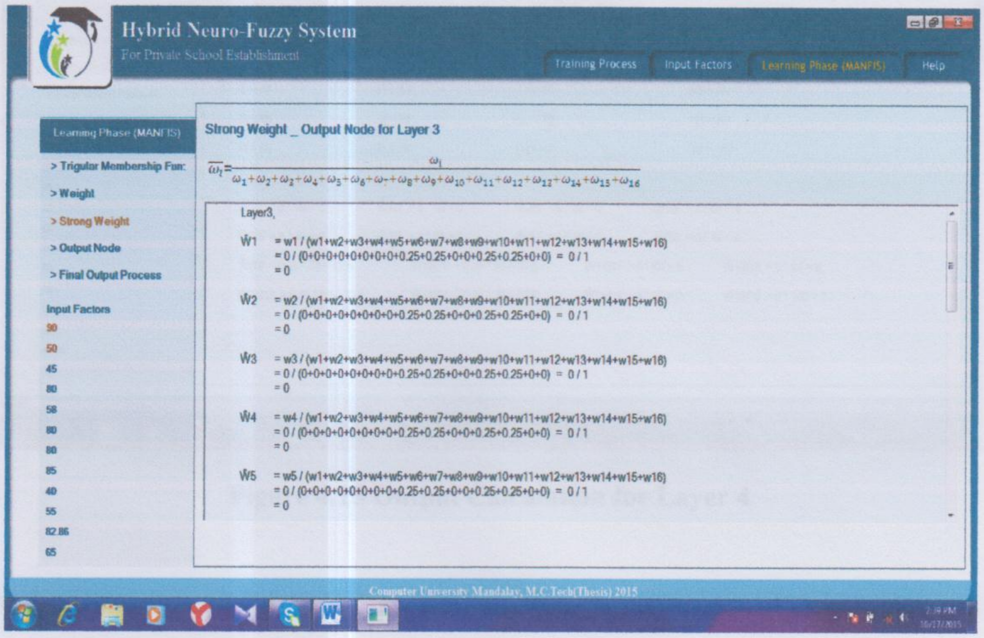


Figure 4.14 Strong Weight Calculation Process

The system calculates strong weights by using equation 3.6 for layer 3. This calculation also must be completed for sixteen times according to input weights values. This process is produced average weight for specific nodes because the current weight is divided by total number of weights for deciding Private School Establishment. Figure 4.14 displays the specific strong weight values.

4.9 Calculations of Output Values

In Figure 4.15, this system calculates specific output values by using equation 3.7. Layer 4 produces the specific output values by using strong weight from layer 3 and input membership values.

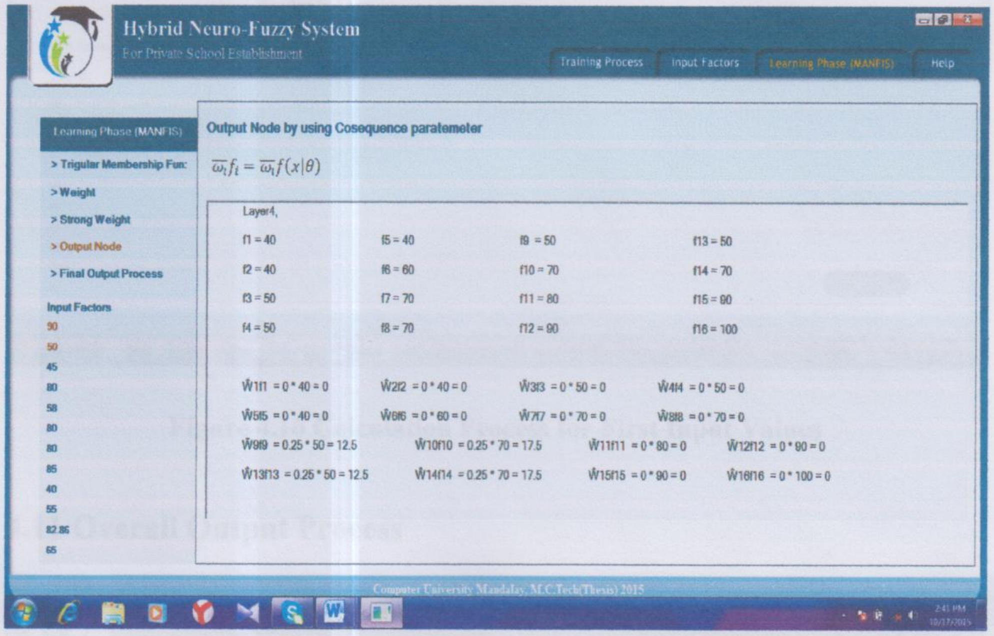


Figure 4.15 Output Calculation for Layer 4

4.10 Consequent Parameters Calculation Process

This process is for first layer output values using equation 3.8. In ANFIS, there is calculation for layer 5 to produce the overall output for specific input. This system calculates the looping process from layer 1 for input nodes to layer 5 for output nodes in Figure 4.16.

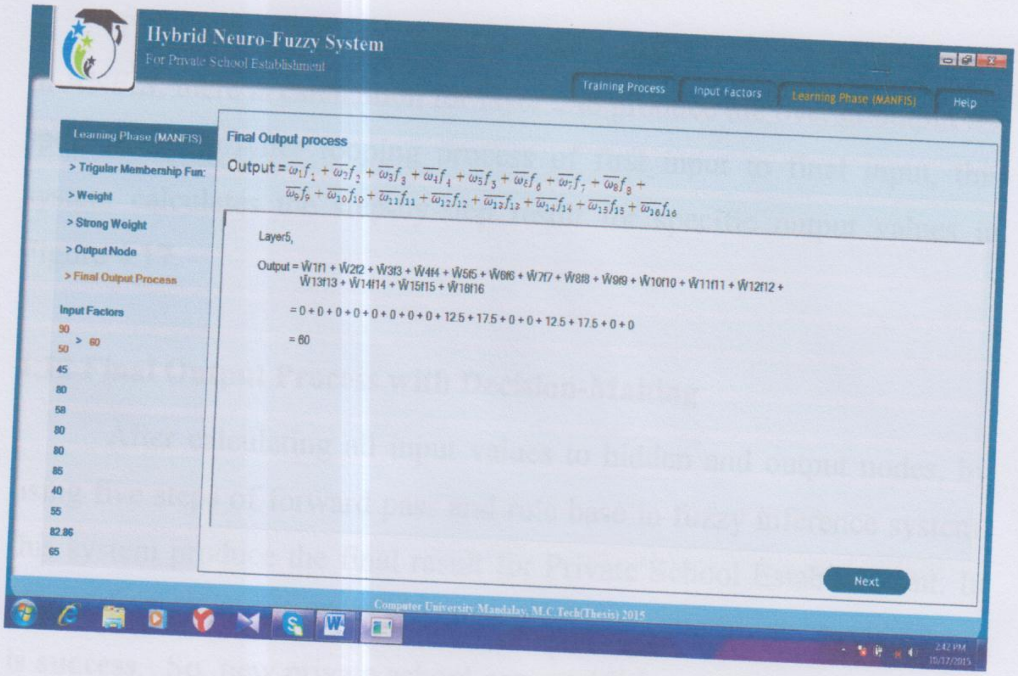


Figure 4.16 Calculation Process for First Input Values

4.11 Overall Output Process

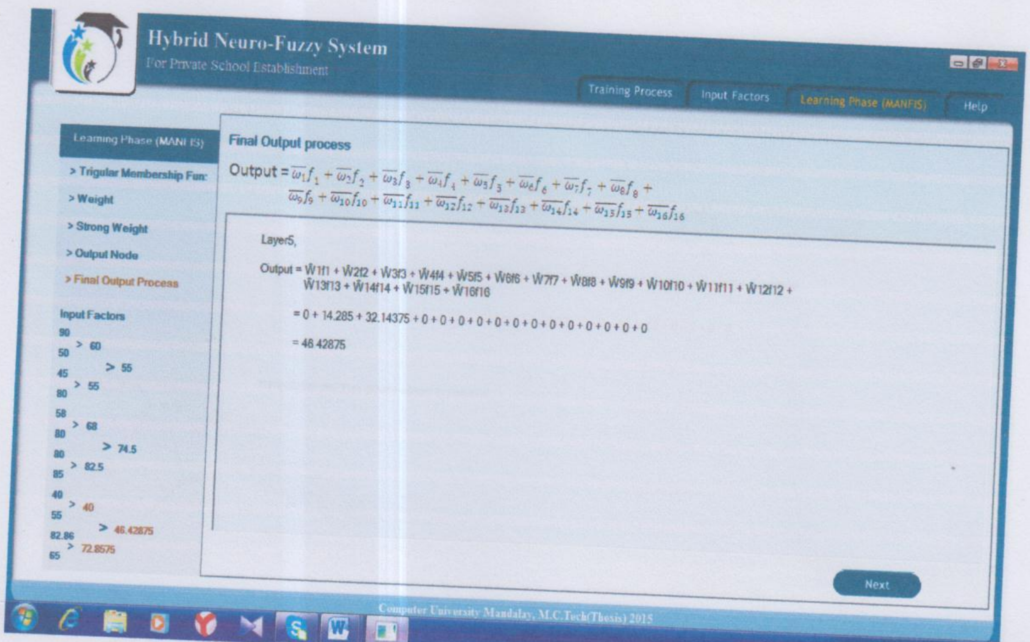


Figure 4.17 Overall Output Process for Secondary Input Values

This process is for Second layer output values using equation 3.8. In ANFIS, there is calculation for layer 5 to produce the overall output for specific input. After looping process of first input to final input, this system calculates the step-by-step result for specific output values in Figure 4.17.

4.12 Final Output Process with Decision-Making

After calculating all input values to hidden and output nodes, by using five steps of forward pass and rule base in fuzzy inference system, this system produce the final result for Private School Establishment. In Figure 4.18, the result is **47.5** and **Congratulation**! **Your private school is success**. So, new private school can establish according to this result. If final result is above 45, new private school can establish and if the result is below 45, new private school is impossible.

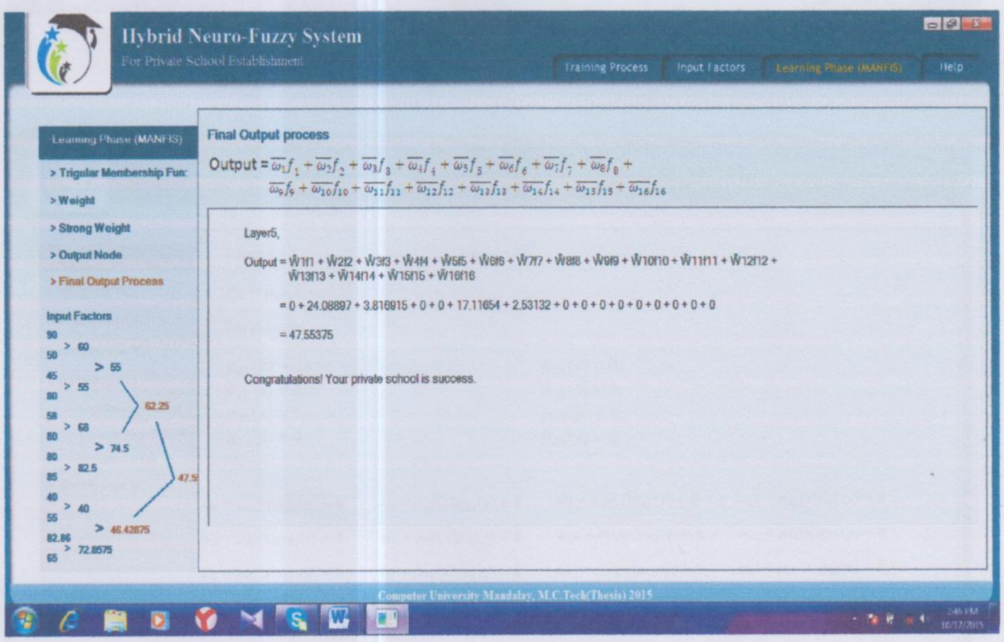


Figure 4.18 Final Output Process with Decision Result

4.13 ANFIS Process for Private School Establishment

In ANFIS, there are five layers from input layer to output layer. The calculation process for each layer and equations are shown in Figure 4.19 to 4.26.

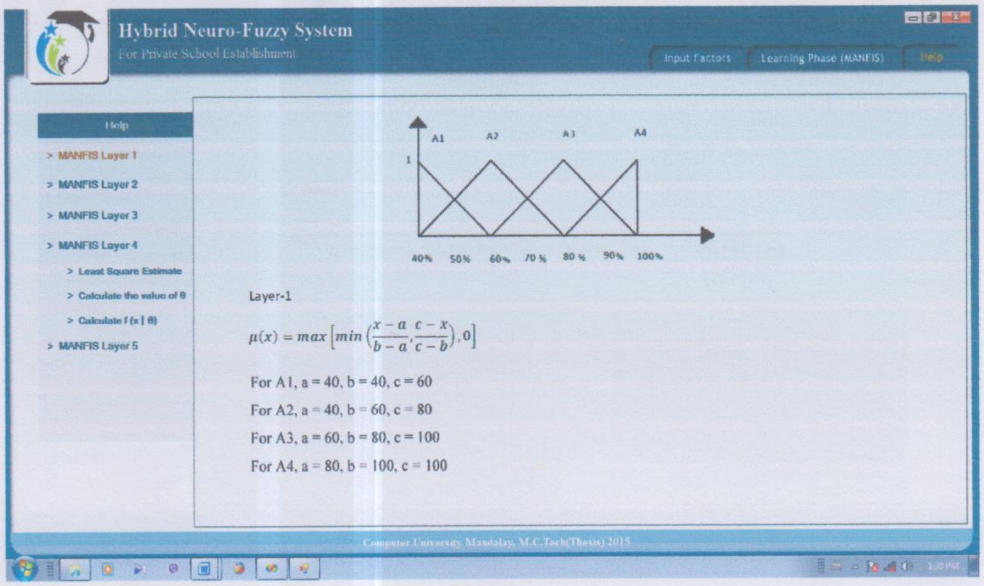


Figure 4.19 ANFIS Layer 1 Process

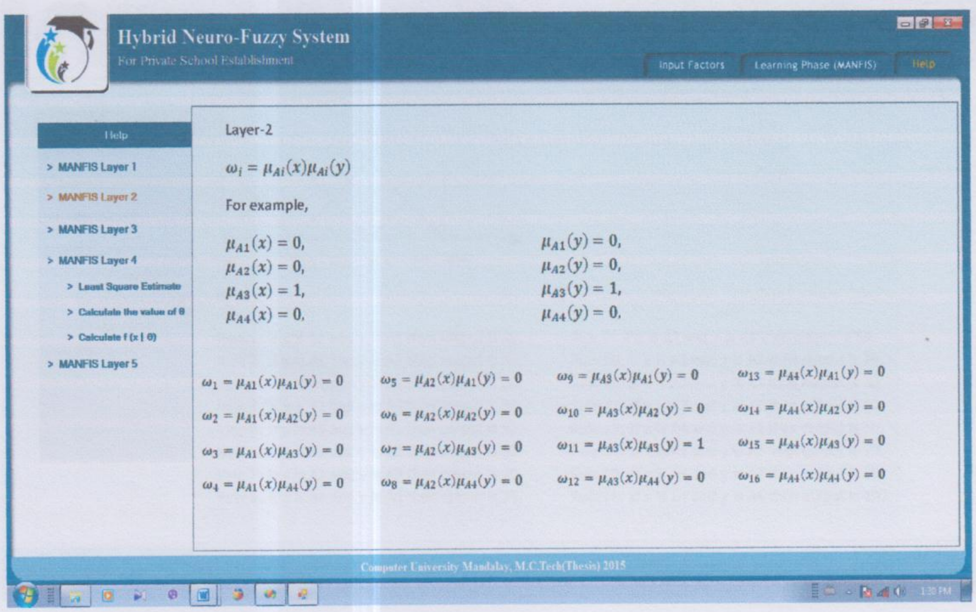


Figure 4.20 ANFIS Layer 2 Processes

In layer 4, there is three step calculation to produce specific output values for input values. And this system uses sixteen kinds of rules in layer 4.

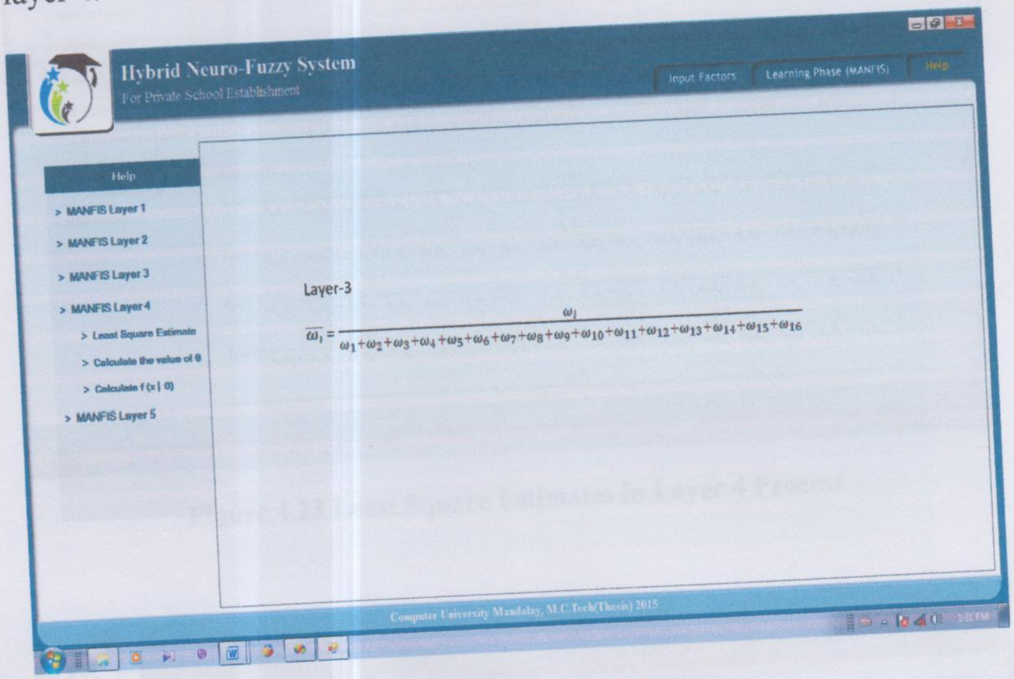


Figure 4.21 ANFIS Layer 3 Processes

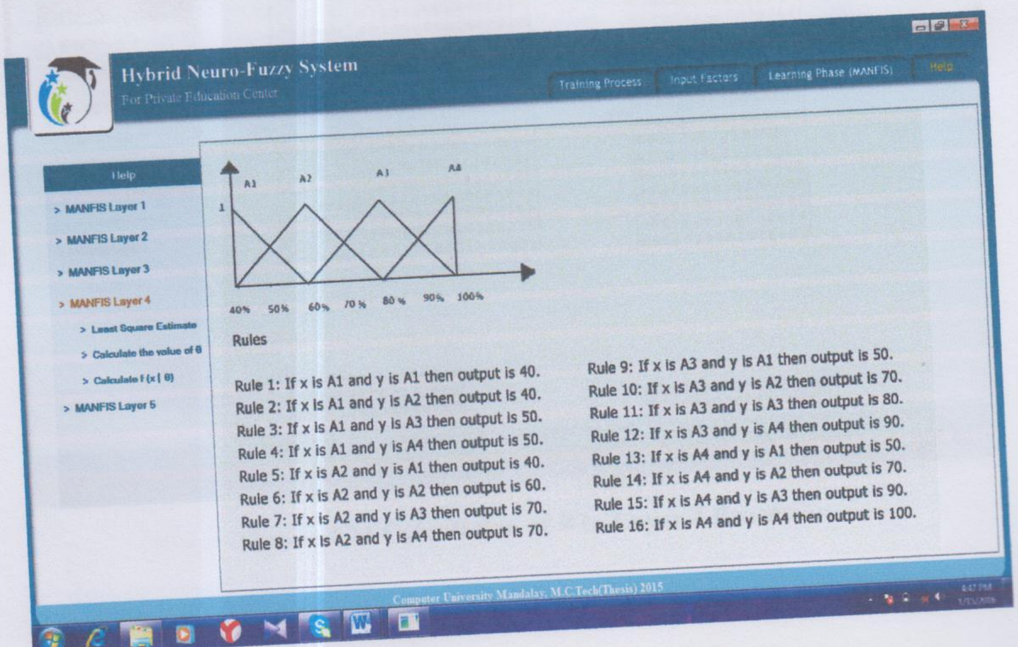


Figure 4.22 Rules in Layer 4 of ANFIS

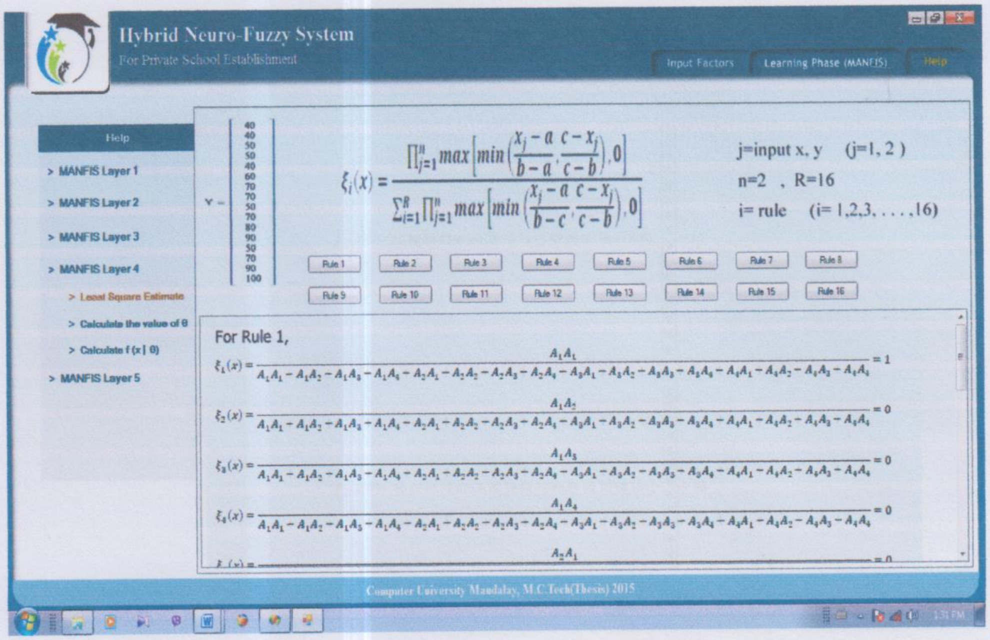


Figure 4.23 Least Square Estimates in Layer 4 Process

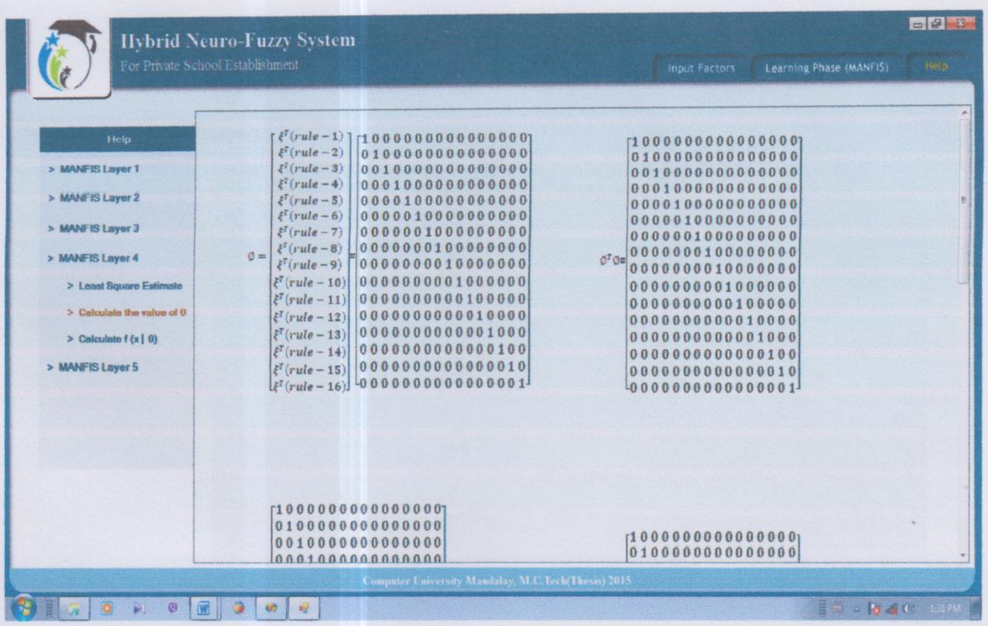


Figure 4.24 Calculation of ϑ in Layer 4 Process

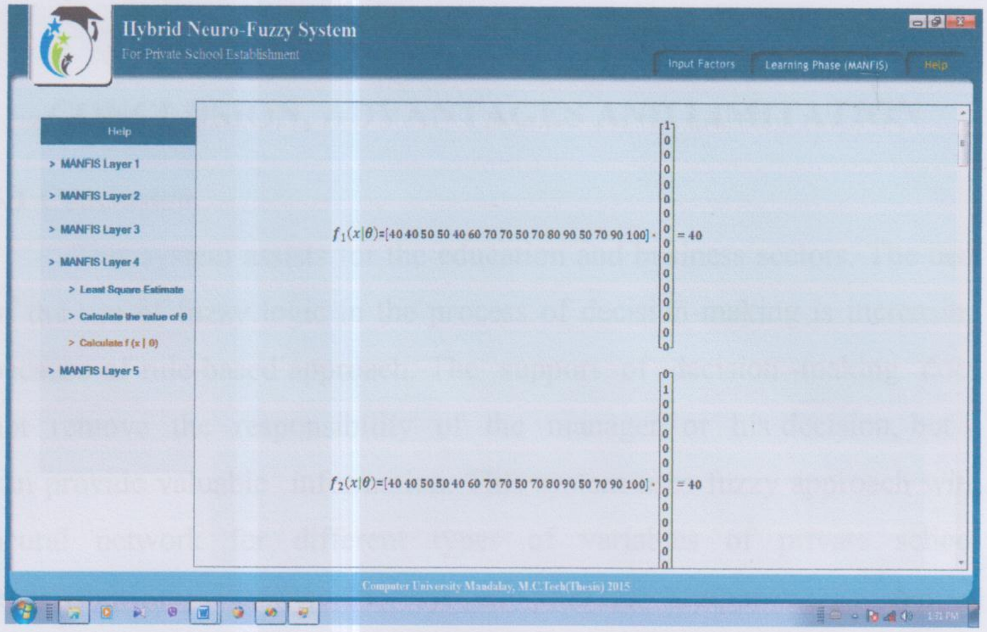


Figure 4.25 Calculation of Output Values in Layer 4 Process

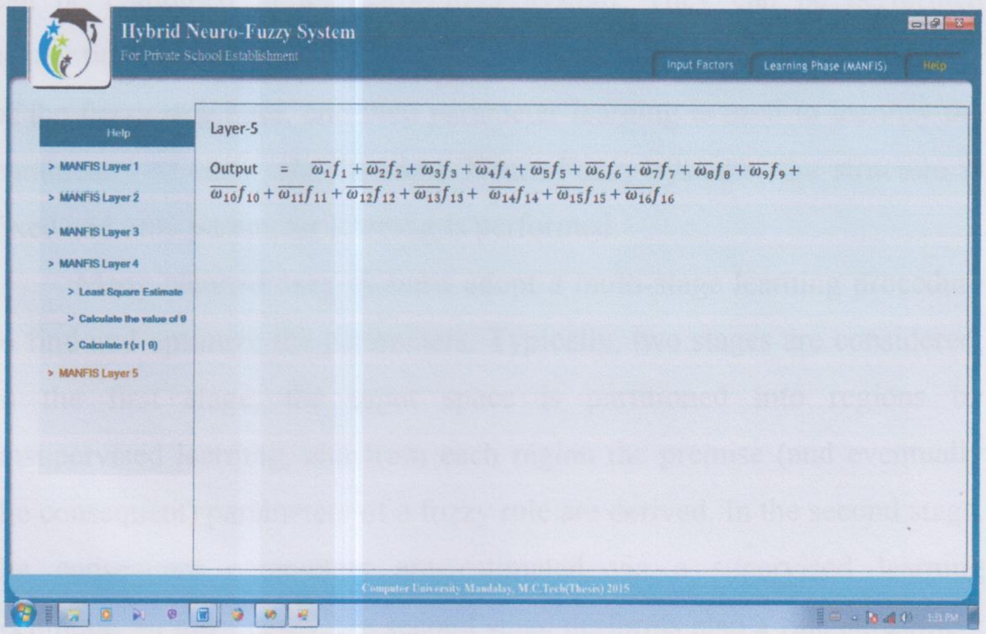


Figure 4.26 Calculation of Overall Output in Layer 5 Process

CHAPTER 5

CONCLUSION, ADVANTAGES AND LIMITATION

5.1 Conclusion

This system assists for the education and business sectors. The task of the use of fuzzy logic in the process of decision-making is increasing because of rule-based approach. The support of decision -making does not remove the responsibility of the manager or his decision, but it can provide valuable information. This system uses fuzzy approach with neural network for different types of variables of private school establishments. Finally, this system produces output result that is successful or impossible for private school establishment.

There are several ways that structure learning and parameter learning can be combined in a Neuro-Fuzzy system. They can be performed sequentially: structure learning is used first to find an appropriate structure of the fuzzy rule base, and then parameter learning is used to identify the parameters of each rule. In some Neuro-Fuzzy systems, the structure is fixed and only parameter learning is performed.

Many Neuro-Fuzzy systems adopt a multi-stage learning procedure to find and optimize the parameters. Typically, two stages are considered. In the first stage, the input space is partitioned into regions by unsupervised learning, and from each region the premise (and eventually the consequent) parameters of a fuzzy rule are derived. In the second stage, the consequent parameters are estimated via a supervised learning technique. In most cases, the second stage performs also a fine adjustment of the premise parameters obtained in the first stage using a nonlinear optimization technique.

5.2 Advantages of System

This system can offer significant savings by shortening the time and decreasing the steps necessary for the evaluation process while deviated in the totality from the traditional system results. On the other hand, the fuzzy approach requires a sufficient expert knowledge for the formulation of the rule base, the combination of the sets and the defuzzification. A typical architecture of an ANFIS, a circle indicates a fixed node, whereas a square indicates an adaptive node. In this connectionist structure, there are input and output nodes, and in the hidden layers, there are nodes functioning as membership functions (MFs) and rules. This eliminates the disadvantage of a normal feedforward multilayer network, which is difficult for an observer to understand or to modify.

5.3 Limitation and Further Extension

The twofold face of fuzzy systems leads to a trade-off between readability and accuracy. Traditional neuro-fuzzy modeling techniques and in general data-driven methods for learning fuzzy rules from data, are aimed to optimize the prediction accuracy of the fuzzy model. This system uses different types of variables as data in private school. The other important requirement to obtain interpretability is to keep the rule base small. In this system, sixteen rules for decision of output. A fuzzy model with interpretable membership functions but a very large number of rules is far from being understandable. For a real-world modeling problem, it is not uncommon to have potential inputs to the model under construction. It is necessary to do input selection that finds the priority of each candidate inputs and uses them accordingly. Inputs are 43 attributes in this system. It can be increased of others factors to establish private school. Once the model structure and parameters have been identified, it is necessary to validate the quality of the resulting model. It is needed for Testing and validation process of the developed ANFIS.

REFERENCES

[1]. Atsalakis S. George , Atsalakis G. Ioanna , "Fruit production forecasting by neuro-fuzzy techniques", Technical University of Crete, Department of Production, Engineering and Management, Crete, University of Ioannina, Department of Business Management on agriculture product and food, Agrinio, Greece,

[2].Azar, Ahmad Taher, "Adaptive Neuro-Fuzzy Systems", Electrical Communication & Electronics Systems Engineering department, Modern Science and Arts University (MSA), 6th of October City, Egypt. ISBN 978-953-7619-92-3, pp. 216, INTECH, Croatia, February 2010.

[3]. Kosko, B., "Neural Networks and Fuzzy Systems". Englewood Cliffs, NJ: Prentice Hall, 1991.

[4].Lipo Wang, Yakov Frayman, "A dynamically generated fuzzy neural network and its application to torsional vibration control of tandem cold rolling mill spindles", Engineering Applications of Artificial Intelligence 15 (2002) 541–550, www.science direct.com

[5]. Mohammad Shafiur Rahmana, M.M. Rashidb, M.A. Hussain. "Thermal conductivity prediction of foods by Neural Network and Fuzzy (ANFIS) modeling techniques food and bioproducts processing". 90 (2012) 333–340 journal homepage: www.elsevier.com/locate/fbp

[6]. Nikola Kasabov, Qun Song, DENFIS: "Dynamic Evolving Neural-Fuzzy Inference System and Its Application for Time-Series Prediction", Department of Information Science University of Otago, P.O Box 56, Dunedin, New Zealand, IEEE Transactions on Fuzzy Systems (2001).

[7].Nsan Gu¨ler , Elif Derya U¨ beyli , "Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients", Department of Electronics and Computer Education, Faculty of Technical Education, Gazi University, 06500 Teknikokullar, Ankara, Turkey, Department of Electrical and Electronics Engineering, Journal of Neuroscience Methods (2005).

[8].Robert Full´er, "Neuro-Fuzzy Methods", E¨otv¨os Lor´and University, Budapest, Neuro-Fuzzy Methods for Modelling & Fault Diagnosis, Lisbon, August 31 and September 1, 2001

[9]. T.Kavitha, M.Chandra Sekhar , CNV Sridhar, "A Neuro-Fuzzy Based Approach to Modeling Affective Customer Satisfaction towards Car Seat Design", International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 2, Issue 6, pp.975-980, November- December 2012.

[10]. Yuanyuan Chai, Limin Jia, and Zundong Zhang, Mamdani "Model based Adaptive Neural Fuzzy, Inference System and its Application", International Journal of Information and Mathematical Sciences 5:1 2009.