Chapter 17

New Areas in Fuzzy Application

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Additional information is available at the end of the chapter

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1. Introduction

"The world is not black and white but only shades of gray." In 1965, Zadeh [1] wrote a seminal paper in which he introduced fuzzy sets, sets with un-sharp boundaries. These sets are considered gray areas rather than black and white in contrast to classical sets which form the basis of binary or Boolean logic. Fuzzy set theory and fuzzy logic are convenient tools for handling uncertain, imprecise, or unmodeled data in intelligent decision-making systems. It has also found many applications in the areas of information sciences and control systems.

In this chapter, we shall discuss two important categories of fuzzy logic nonlinear applications: “Control” and “Trending and Prediction”. With respect to Fuzzy Control application, among the huge applications that were published under this category, two new applications are selected in this chapter to focus on the Hierarchal Control application with “multi-input” “multi-output” signals, and another application is selected as application of smart electrical grid. However, for Fuzzy Trending and Prediction Application, c-Mean Fuzzy Cluttering technique is discussed as an introduction for Fuzzy trending algorithm, and then two different applications are introduced. The first application discusses very nonlinear problem to predict the rate of accident for labours work in a construction sector, and the second application is to find a fault in complicated electrical network. All these new applications for fuzzy control and fuzzy trending recognition has been found after year 2000.

2. Control

Control is one of the main the application for the fuzzy controller, especially for the applications that can be easily expressed by linguistically. Many machines now in the market are fuzzy machines. Also the fuzzy logic has take place in the DCS’s and PLC’s as recognized function to build process controllers. In this chapter we shall select three applications as an example for the new application of fuzzy logic in the control.

2.1. Fuzzy control design for gas absorber system

In this section, the chapter shall present the research efforts that have been carried out on the control of gas absorbers/gas reactors. It shall also introduce the new approach to a fuzzy control design for a typical gas absorber system. The approach shall incorporate a linear state-estimation to generate the internal knowledge-base that shall store input-output pairs. This collection of pairs shall be then utilized to build a feedback fuzzy controller for the gas absorber.

2.1.1. Background

A major direction in systems engineering design has been focused on the use of simplified mathematical models to facilitate the design process. This constitutes the so-called model-based system design approach, an overview of the underlying techniques can be found in [2]. Most of the available results have thus far overlooked the operational knowledge of the dynamical system under consideration. On the other hand, a knowledge-based system approach [8] has been suggested to deal with the analysis and design problems of different classes of dynamical systems by incorporating both the simplest available model as well as the best available knowledge about the system. For single physical systems, one of the earlier efforts along this direction has been on the development of an expert learning system; see [4-7] and their references. An alternative approach has been on integrating elements of discrete event systems with differential equations [3].

A third approach has been through the use of fuzzy logic control by successfully applying fuzzy sets and systems theory [9]. In the cases where understood there is no acceptable mathematical model for the plant, fuzzy logic controllers [10] are proved very useful and effective. They are generally base on using qualitative rules of thumb, that is, qualitative control rules in terms of vague and fuzzy sentences. It has been pointed out [11] that fuzzy control systems possess the following features:

Hierarchical ordering of fuzzy rules is used to reduce the size of the inference engine. Real-time implementation, or on-line simulation, of fuzzy controllers can help reduce the burden of large-sized rule sets by fusing sensory data before imputing the system's output to the inference engine.

This section is presenting a new approach to fuzzy control design for a gas absorber system. It provides a new and efficient procedure to construct the inference engine by incorporating a linear state-estimator in generating and storing input-output pairs. This collection of pairs is then utilized to build a feedback fuzzy controller. By fine-tuning of the controller parameters, it is shown that the gas absorber system has always a guaranteed stability. Numerical simulation of a six-order gas absorber is carried out and the obtained results show clearly that the proposed estimator-fuzzy controller scheme yields excellent performance.

2.1.2. A Gas Absorber System

A. Brief Account

Separation processes play an important role in most chemical manufacturing industries. Streams from chemical reactors often contain a number of components; some of these components must be separated from the other components for sale as a final product, or for use in another manufacturing process. A common example of a separation process is gas absorption (also called gas scrubbing, or gas washing) in which a gas mixture is contacted with a liquid (the absorbent or solvent) to selectively dissolve one or more components by mass transfer from the gas to the liquid. Absorption is used to separate gas mixtures; remove impurities, contaminants, pollutants, or catalyst poisons from a gas; or recover valuable chemicals. In general, the species of interest in the gas mixture may be all components, only the component(s) not transferred, or only the component(s) transferred. Absorption is frequently conducted in trayed towers (plate columns), packed columns, spray towers, bubble columns, and centrifugal contactors. A trayed tower is a vertical, cylindrical pressure vessel in which vapor and liquid, which flow counter-currently, are contacted on a series of metal trays or plates; see Fig. 1. Components that enter the bottom of the tower is the gas feed stream are absorbed by the liquid stream, that flows across each tray, over an outlet weir and into a down-comer, so that the gas product stream (leaving the top of the tower) is more pure.

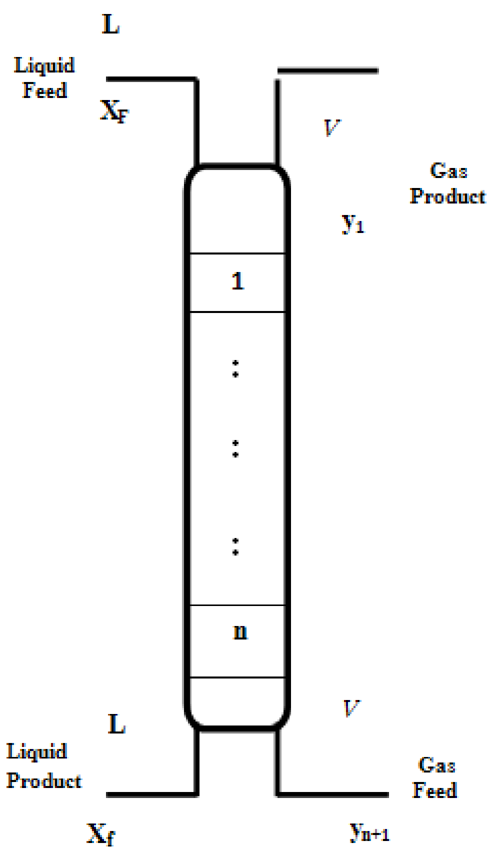

Figure 1. Gas absorption column, n stages

B. Assumptions and definitions

The basic assumptions used are:

A1) The major component of the liquid stream is inert and does not absorb into the gas stream.
A2) The major component of the gas stream is inert and does not absorb into the liquid stream.
A3) Each stage of the process is an equilibrium stage, that is, the vapour leaving a stage is in thermodynamic equilibrium with the liquid on that stage.
A4) The liquid molar holdup is constant.

We now introduce the following variable definitions:

- L = moles inert liquid per time: = liquid molar flow rate.
- V= moles inert vapor per time: = vapor molar flow rate
- M= moles liquid per stage: = liquid molar holdup per stage
- W= moles vapor per stage: = vapor molar holdup per stage
- x_j= moles solute (stage j) per mole inert liquid (stage j)
- y_j= moles solute (stage j) per mole inert vapor (stage j)

C. Dynamic model

The concept of an equilibrium stage is important for the development of a dynamic model of the absorption tower. An equilibrium stage is represented schematically in Fig. 2. The total amount of solute on stage j is the sum of the solute in the liquid phase and the gas phase (that is, $M x_j + W y_j$). Thus the rate of change of the amount of solute is $d(M x_j + W y_j)/dt$ and the component material balance around stage j can be expressed as:

$$\begin{aligned} \frac{d(M x_j + W y_j)}{dt} &= L x_{j-1} + V y_{j+1} - L x_j - V y_j \\ \frac{dM x_j}{dt} &\cong L x_{j-1} + V y_{j+1} - L x_j - V y_j \end{aligned} \tag{1}$$

where we assumed that in accumulation, liquid is much more dense than vapor. Under assumption A4), then (1) simplifies into:

$$\frac{d x_j}{dt} \cong \frac{L}{M} x_{j-1} + \frac{V}{M} y_{j+1} - \frac{L}{M} x_j - \frac{V}{M} y_j \tag{2}$$

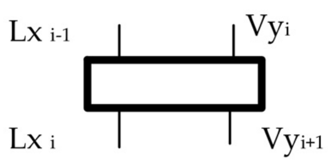

Figure 2. A typical gas absorption stage

Under assumption A3), we let

$$y_j = d \; x_j \tag{3}$$

which expresses a linear relationship between the liquid phase and gas phase compositions at stage j with d being an equilibrium parameter. Using (3) into (2) and arranging we get:

$$\frac{d\,x_j}{dt} = \frac{L}{M} x_{j-1} - \frac{(L+V\,d)}{M} x_j - \frac{V\,d}{M} x_{j+1} \tag{4}$$

For n-stage gas absorber, (4) is valid for j =2,…,n-1. At the extreme stages, we have:

$$\frac{d\,x_1}{dt} = -\frac{(L+V\,d)}{M} x_1 - \frac{V\,d}{M} x_2 + \frac{L}{M} x_f \tag{5}$$

$$\frac{d\,x_n}{dt} = -\frac{(L+V\,d)}{M} x_n + \frac{L}{M} x_{n-1} + \frac{V}{M} y_{n+1} \tag{6}$$

where xf and yn+1 are the known liquid and vapor feed compositions, respectively.

On combining (3), (4),(5) and (6), we reach the state-space model:

$$\dot{x}(t) = A\; x(t) + B\,u(t), \qquad y(t) = C\,x(t) \tag{7}$$

where A an (nxn) system matrix with a triangular structure, B is an (nxm) input matrix and C is an (nxp) output matrix given by:

$$A = \begin{bmatrix} -\frac{L+M}{M} & \frac{Vd}{M} & 0 & 0 & 0\;0\cdots & 0 \\ \frac{L}{M} & -\frac{L+Vd}{M} & \frac{Vd}{M} & 0 & 0\;\cdots & 0 \\ 0 & \frac{L}{M} & -\frac{L+Vd}{M} & \frac{Vd}{M} & 0\;\cdots & 0 \\ 0 & & \ddots & & & 0 \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \\ 0 & & & & \frac{L}{M} & -\frac{L+Vd}{M} \end{bmatrix} \tag{8}$$

$$B = \begin{bmatrix} \dfrac{L}{M} & 0 \\ 0 & 0 \\ \vdots & \vdots \\ \vdots & \vdots \\ \vdots & \vdots \\ \vdots & \vdots \\ \vdots & \dfrac{V}{M} \end{bmatrix} \tag{9}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{10}$$

2.1.3. Fuzzy controller design

The design of a fuzzy controller can be implemented by the following steps:

Step1:

Supposed that the output y (t) takes values in the interval $U = [\alpha, \beta] \subset R$. Define 2N+1 fuzzy function A^l in U that are consistent and complete with the triangular membership functions shown in Fig. 3. That is, we use the N fuzzy sets A^1, ---, A^N to cover the negative interval $[\alpha, 0)$, the other N fuzzy sets A^{N+2},---, A^{2N+1} to cover the positive interval $(0, \beta]$, and choose the center x N+1 of fuzzy set A^{N+1} at zero.

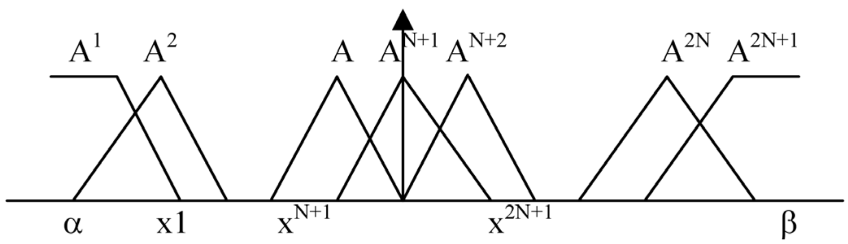

Figure 3. Membership functions for the fuzzy controller.

Step 2:

Consider the following 2N+1 fuzzy IF-THEN rules:

$$\text{IF y is } A^1, \text{ THEN u is } B^1 \tag{11}$$

Where l = 1, 2, ---, 2N+1, and centers $\overline{y^1}$ of fuzzy set B^l are chosen such that,

$$\overline{y^1} \begin{cases} \leq 0 & \text{for } 1=1,\cdots,N \\ = 0 & \text{for } 1=N+1 \\ \geq 0 & \text{for } 1=N+2,\cdots,2N+1 \end{cases} \tag{12}$$

Step 3:

Design the fuzzy controller from the 2N+1 fuzzy IF THEN rules (11) using product inference engine, singleton fuzzifier and center average defuzzifier; that is, the designed fuzzy controller is

$$v=-f(y)=\frac{\sum_{1=1}^{2N+1}\overline{y^{1}}\mu A^{1}(y)}{\sum_{1=1}^{2N+1}\mu A^{1}(y)} \tag{13}$$

Where $\mu_A{}^{l}(y)$ are shown in Fig. 3 and y^{1} satisfy $\bar{y}$ (12).

To estimate the range of the input-output pairs $\{v_i, y_i\}$, full order estimator [2] can be used.

2.1.4. Simulation studies

Consider a gas absorber system with the following parameters: L=80, M=200, V=100 and d=0.5.

Thus,

$$\frac{L+Vd}{M}=-0.65, \frac{L}{M}=0.4, \frac{V\ d}{M}=0.25, \frac{V}{M}=0.5$$

A MATLAB program is written to simulate the gas absorber system. Different positive and negative step input are applied to estimate the outputs. The results of two cases are illustrated in Fig. 4 and Fig. 5. The tracking behaviour of the outputs is shown.

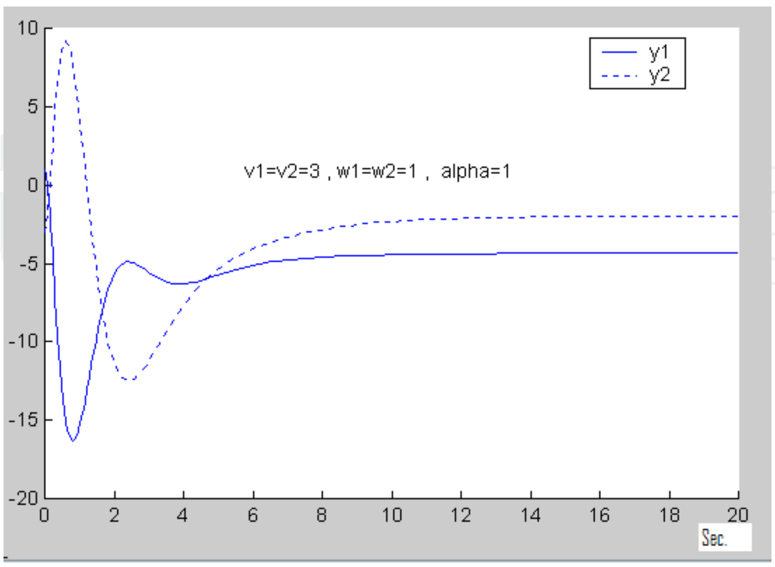

Figure 4. Output response with positive step input signal

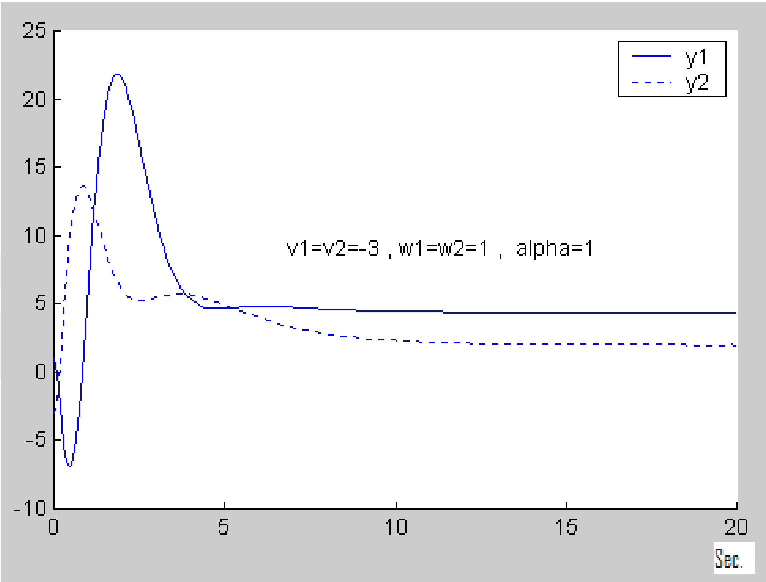

Figure 5. Output response with negative step input signal

From the input-output pair obtained, the behaviour of the system is examined and the ranges of its outputs (controllers' inputs) are predicted. Fig. 6 illustrates a block diagram of the gas absorber and the fuzzy controller array.

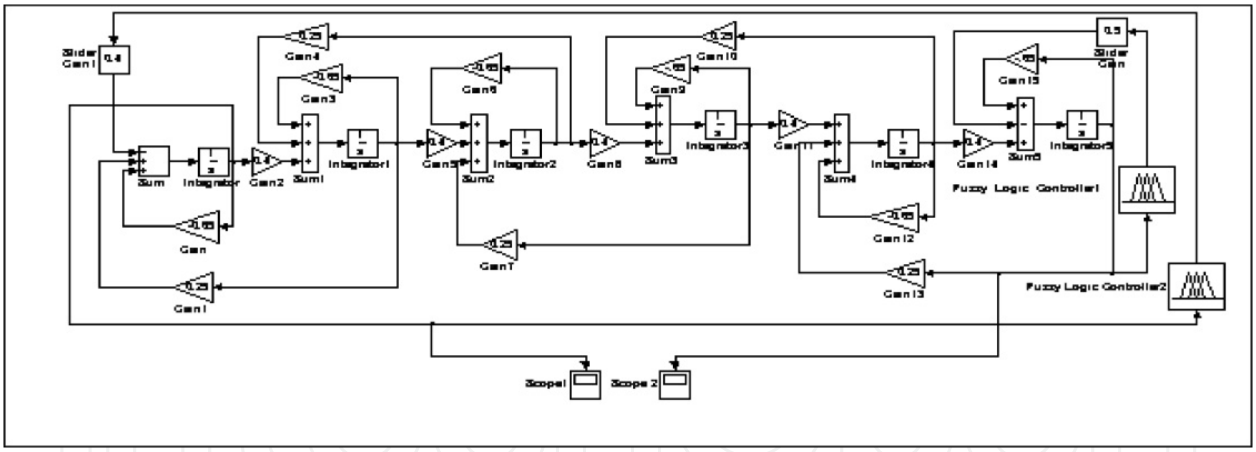

Figure 6. Block Diagram of gas absorber system and the fuzzy controllers

To control the response of the gas absorber, the range of linguistic values of the output of each feedback fuzzy controller is tuned between (– 3) and (3). Comparison between the output response with fuzzy controller (when the number of linguistic values of the controller input – output pair is three) and without controller is illustrated in Fig.7 and Fig.8.

In Fig.7, the controller is tuned to interfere the natural decay of the system. In Fig. 8, the fuzzy controller is adjusted to improve the response of the gas absorber. It is noted that the response of controlled system has less overshoot, less steady state error and faster compared to the uncontrolled system.

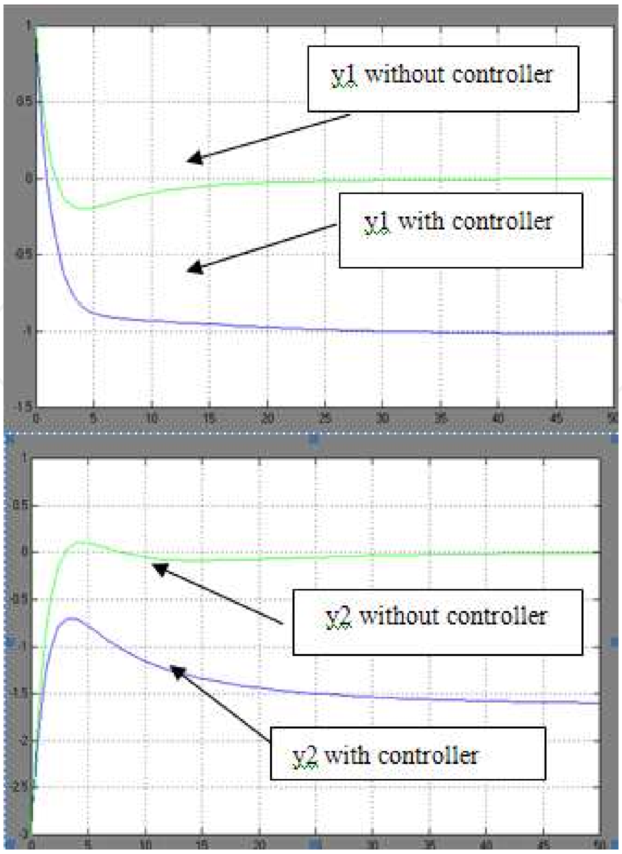

Figure 7. Controller is tuned to interfere the natural decay of the system

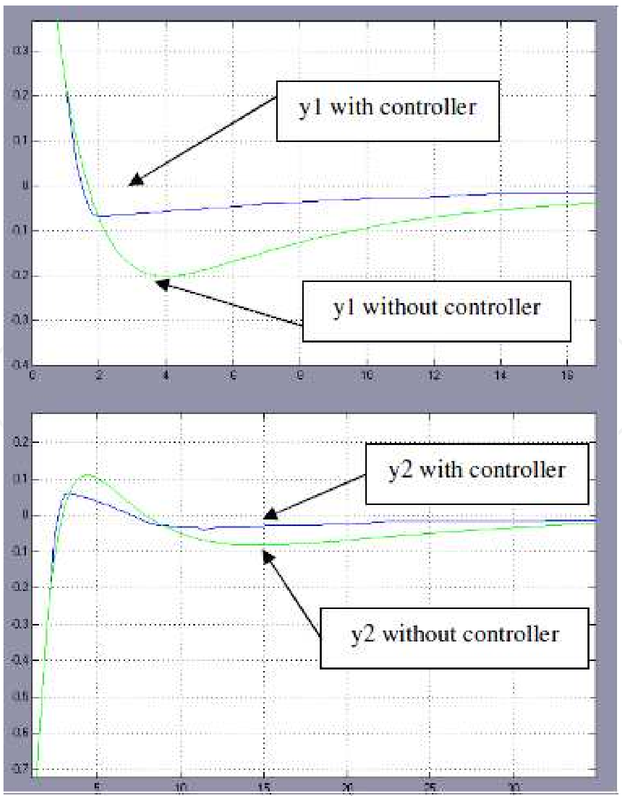

Figure 8. The controller is tuned to improve the response of the system.

2.1.5. Discussion

This section has presented a new and simple fuzzy controller for a gas absorber system to enhance the response of the output. The simulation results have shown that the controller guarantees well-damped behaviour of the controlled gas absorber system.

2.2. Large scale fuzzy controller

In this section, we shall develop a new approach to the control of interconnected system using fuzzy system theory. The approach shall be based on incorporating a group of local estimators on the system level to generate the input-output database. An array of feedback fuzzy controllers shall then be designed to ensure the asymptotic stability of the closed loop system. The developed technique shall be applied to an unstable large-scale system and extensive simulation studies shall be carried out to illustrate the potential of this new approach..

2.2.1. Background

In control engineering research, problems of decentralized control and stabilization of interconnected systems are receiving considerable interest in recent years [14,15] where most of the effort is focused on dealing with the interaction patterns. It is concluded that a systematic approach to deal with the problems of interconnected systems is twofold: first is to base the analysis and design effort on the subsystem level using conventional control methods and second is to deal with interactions effectively. These methods are facilitated, in general, by virtue of several mathematical tools including linearization, delay approximation, decomposition and model reduction. This constitutes the so-called model-based control system approach for which we have seen numerous techniques [16]. Most of the available results have so far overlooked the operational knowledge of the interconnected system under consideration. In [17], a knowledge-based control system approach has been suggested to deal with the analysis and design problems of interconnected systems by incorporating both the simplest available model as well as the best available knowledge about the system. For single physical systems, one of the earlier efforts along this direction has been on the development of an expert learning system [18-19]. An alternative approach has been on integrating elements of discrete event systems with differential equations [20]. A practically-supported third approach has been through the use of fuzzy logic control by successfully applying fuzzy sets and systems theory [21].

For interconnected systems, the foregoing approach motivates the research into intelligent control by combining techniques of control and systems theory with those from artificial intelligence. The main focus should be on integrating a knowledge base, an approximate (humanlike) reasoning and/or a learning process within a hierarchical structure.

Fuzzy logic controllers [23-25] are generally considered applicable to plants that are mathematically poorly understood (there is no acceptable mathematical model for the plant) and where experienced human operators are available for satisfactorily controlling the plant and providing qualitative "rules of thumb" (qualitative control rules in terms of vague and fuzzy sentences).

A concerted effort has been made to formally reduce the size of the fuzzy rule base to make fuzzy control attractive to interconnected systems. Two of the difficulties with the design of any fuzzy control system are:

- The shape of the membership functions.
- The choice of fuzzy rules.

The properties that a fuzzy membership function is used to characterize are usually fuzzy. Therefore, we may use different membership functions to characterize the same description.

Conceptually, there are two approaches to determine a membership function. The first approach is to use the knowledge of human experts. Usually this approach can only give a rough formula of the membership function; fine-tuning is required. In the second approach, data are collected from various sensors to determine the member ship functions. Specifically, the structures of the membership functions are specified first, then fine-tuning of the membership function parameters should be implemented based on the collected data [8].

In this section, we contribute to the further development of intelligent control techniques of interconnected systems. It provides a new approach to fuzzy control design for interconnected system. The approach consists of two stages: In the first stage, a group of local state estimator is constructed to generate the data base of input-output pairs. In the second stage, an array of feedback fuzzy controllers is designed and implemented to ensure the asymptotic satiability of the interconnected system. Simulation studies on a large-scale system with unstable eigenvalus are carried out to illustrate the features and capability of this new approach.

2.2.2. State estimation of interconnected systems

In the sequel, the terms large-scale and interconnected are used interchangeable. The term large scale system (LSS) does not have a unique established meaning, but it covers systems that possess several particular feature, such as multiple subsystem, [14,17] multiple control, multiple objectives, decentralized and/or hierarchical information structures. Any LSS includes many variables but their control is faced by a well-know fact [16] that the states are not always available for measurement and state must be estimated.

Many authors have considered the state estimation of large-scale systems in input decentralized fashion. Here we summarize one convenient algorithm [15]. Let the state model of the ith subsystem described by

$$\dot{x}_i(t) = A_i x_i(t) + B_i u_i(t) + \Sigma^N G_{ij} x_j \qquad (14)$$

$$y_i(t) = C_i x_i(t),\ i,j = 1,\ 2,\ \ldots\ldots\ N \qquad (15)$$

Where all vectors and matrices are appropriately defined and $g_i(.)$ is the interaction function between the ith subsystem and the rest of the system. It is considered that (C_i, A_i) is completely observable for i = 1, 2, …….. N.

The following algorithm finds the optimal states of a large-scale system based on decentralized estimation and control [17]:

Algorithm 1:

Step 1:

Read the matrices A_i, Bi and select $Q_i \geq 0$ and $R_i > 0$ as weighted matrix.

Step 2:

Solve the following 2N algebraic Riccati equations for H_i, K_i

$$Hi(A^T{}_i + \alpha I_i) + (A_i + \alpha I_i)H_i - H_i D_i H_i + Q_i = 0 \tag{16}$$

$$Ki(A^T{}_i + \alpha I_i) + (A_i + \alpha I_i)K_i - K_i S_i K_i + Q_i = 0 \tag{17}$$

Where $D_i = C^T{}_i C_i$, $S_i = B_i R^{-1}{}_i B^T$

Step 3:

Integrate the following set of N simultaneous equation for $e_i(t)$, I = 1, 2 …. N, using the initial condition $e_i(0) = x_i(0)$

$$\begin{pmatrix} \dot{e}_1 \\ \vdots \\ \dot{e}_N \end{pmatrix} = \begin{pmatrix} A_1\text{-}S_1K_1 & \cdots & G_{1N} \\ \vdots & \ddots & \\ G_{N_1} & & A_N\text{-}H_ND_N \end{pmatrix} \begin{pmatrix} e_1 \\ \vdots \\ e_N \end{pmatrix} + \begin{pmatrix} B_1v_1 \\ \vdots \\ B_Nv_N \end{pmatrix} \tag{18}$$

Step 4:

Integrate the following set of n simultaneous equations for x 1(t), i = 1, 2, ….. N

$$\begin{pmatrix} \dot{x}_1 \\ \vdots \\ \dot{x}_N \end{pmatrix} = \begin{pmatrix} A_1\text{-}S_1K_1 & \cdots & G_{1N} & S_1K_1 \cdots & 0 \\ \vdots & & & \ddots & \\ G_{N_1} & & A_N\text{-}S_NI_N & 0 & S_NK_N \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix} + \begin{pmatrix} B_1v_1 \\ \vdots \\ B_Nv_N \end{pmatrix} \tag{19}$$

$\dot{x}_N$ G_{N1} A_N - $S_N I_N$ 0 $S_N K_N$ x_N $B_N v_N$

Step 5:

Generate the input-output pairs $\{v_i, \hat{y}_i = c_i \hat{x}_i\}$.

2.2.3. Interconnected system

Assume the following interconnected system of order 10 [17]:

$$A=\begin{pmatrix} -1.5 & -0.3 & -0.25 & 0.1 & 0.5 & r1_{11} & r1_{12} & r1_{13} & r1_{14} & r1_{15} \\ 0.1 & 0 & 0 & -0.2 & 0 & r1_{21} & r1_{22} & r1_{23} & r1_{24} & r1_{25} \\ 0 & 0.2 & -1 & 0 & 0.4 & r1_{31} & r1_{32} & r1_{33} & r1_{34} & r1_{35} \\ 0.6 & -0.1 & -0.25 & -2 & 0 & r1_{41} & r1_{42} & r1_{43} & r1_{44} & r1_{45} \\ 0.4 & 0.2 & 1 & 0.5 & 0.1 & r1_{51} & r1_{52} & r1_{53} & r1_{54} & r1_{55} \\ r2_{11} & r2_{12} & r2_{13} & r2_{14} & r2_{15} & -1.5 & -0.3 & -0.25 & 0.1 & 0.5 \\ r2_{21} & r2_{22} & r2_{23} & r2_{24} & r2_{25} & 0.1 & 0 & 0 & -0.2 & 0 \\ r2_{31} & r2_{32} & r2_{33} & r2_{34} & r2_{35} & 0 & 0.2 & -1 & 0 & 0.4 \\ r2_{41} & r2_{42} & r2_{43} & r2_{44} & r2_{45} & 0.6 & -0.1 & -0.25 & -2 & 0 \\ r2_{51} & r2_{52} & r2_{53} & r2_{54} & r2_{55} & 0.4 & 0.2 & 1 & 0.5 & 0.1 \end{pmatrix} \tag{20}$$

$$B=\begin{pmatrix} 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{21}$$

$$C=\begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \end{pmatrix} \tag{22}$$

Which is considered to be composed of two-coupled subsystems; each of order 5. The coupling parameters are $r1_{jk}$ and $r2_{jk}$ where j and k take values of 1,2,3,4 and 5. In the sequel, we refer to the structure of the interconnected system model as:

$$\dot{x}=\begin{pmatrix} A11 & \cdots & G12(\underline{r1}) \\ \vdots & \ddots & \\ G21(\underline{r2}) & & A22 \end{pmatrix} x+\begin{pmatrix} B1 \\ \vdots \\ B2 \end{pmatrix} v \tag{23}$$

Where G12(r1) and G21(r2) are the coupling mtrices.

For a typical values [4] of $r1_{15}$=-0.1, $r1_{24}$=0.1, $r1_{42}$=0.2, $r2_{22}$=0.1,$r2_{42}$=0.15,$r2_{51}$=0.11 and allothe values of coupling parameters are zeros, we examined the stability of the system by computing the eigenvalues of matrix A. They are {-1.0915, -1.0641, 0.477 + j0.0206, 0.477 – j0.00206, 0.022 + j0.0544, 0.022 – j0.0544, -1.8709 + j0.1713, -1.8709 – j0.1713, -1.9306 + j0.1413, -

1.9306 – j0.1413}, and it is quite clear that there are four eigenvalues lie in the open right half of the complex plane and thus the interconnected system is unstable. Further, it is easy to check that the interconnected system is both controllable and observable.

2.2.4. Estimation of the system state variables and outputs

A Matlab program is written to implement the computational Algorithm (1) of section 1.2.2 on the interconnected system. Different positive and negative step input are applied to estimate the outputs. The results of two cases are illustrated in Fig. 9 and Fig. 10 It is observed that the outputs tend to track conveniently the input signals.

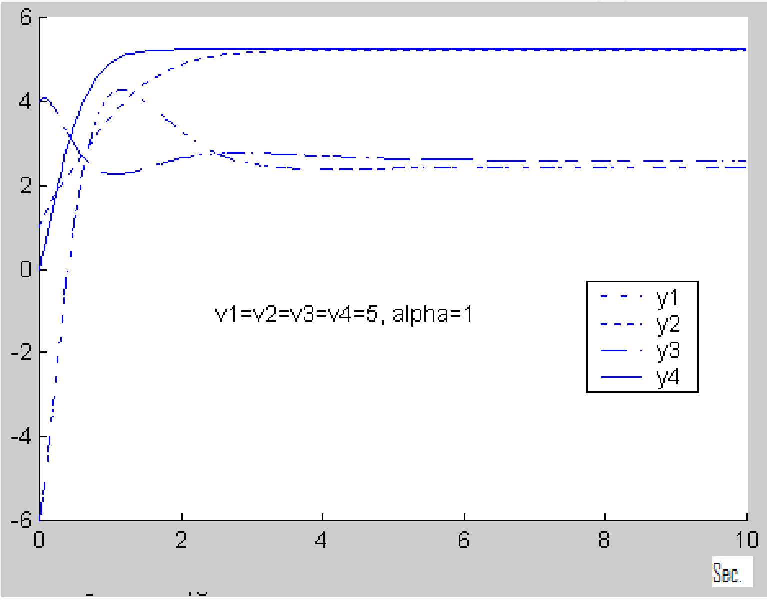

Figure 9. Simulation Results for case 1.

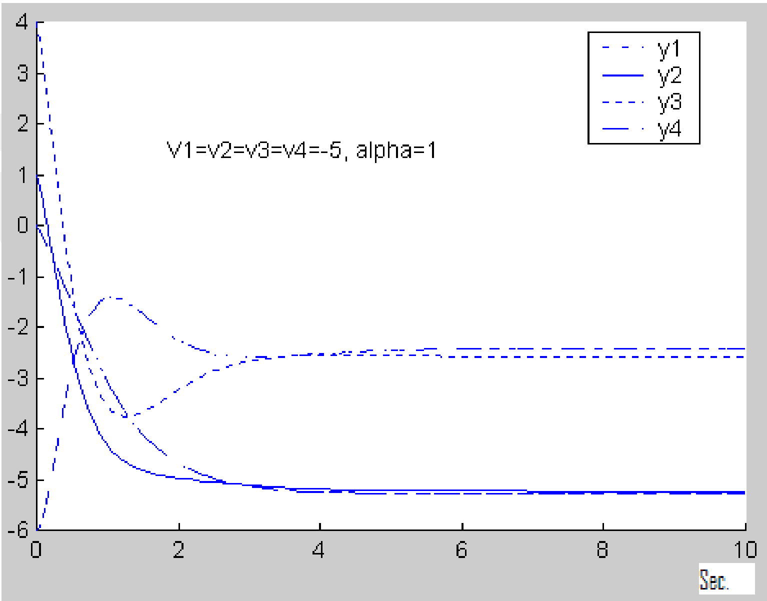

Figure 10. Simulation Results for case 2.

2.2.5. Design of an array of fuzzy controller

We are going to treat the interconnected system at hand as being composed of two identical and coupled subsystems. The control system to be designed is such that each subsystem has its own fuzzy negative feedback controller which its input being the output of the respective subsystem (Fig. 11). Each subsystem fuzzy controller is constructed using two fuzzy systems.

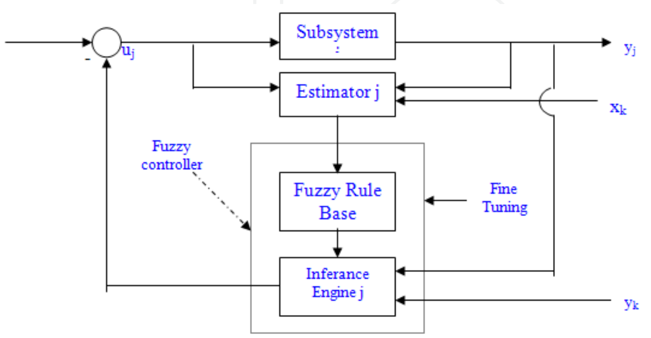

Figure 11. Block diagram of the proposed fuzzy feedback controller array.

In order to build each fuzzy controller, the following steps are implemented:

Step 1:

The range of the inputs to each fuzzy controller [α_i, β_i] are driven from the estimated value of the respective subsystem outputs, where i = 1, 2, 3, 4.

Step 2:

2N+1 fuzzy set $M^L{}_i$ in [α_i, β_i] that are normal, consistent and complete with triangular membership functions [24], are defined for each controller, where L = 1, 2--, 2N_i+1. That is we use N_i fuzzy set $M^1{}_i$, ---, M_i^{Ni} to cover the negative internal [α_I, 0), the other N_i fuzzy sets M_i^{Ni+2}, ---, M_i^{2Ni+1} to cover the positive internal (0, β], and the center of fuzzy set M_i^{Ni+1} at zero.

Step 3:

The following 2N_i+1 rules are considered

$$\text{IF } y_{ai} \text{ is } M_i^L \text{ or } y_{bi} \text{ is } M_i^L \text{ then u is } K_i^L$$

Where L = 1, 2,---, 2N_i+1, and a_i, b_i are the input to the fuzzy controller i, and the center y_{ai}^L and $y_b{}^{-L}$ of the fuzzy set k_i^L are chosen such that

$$y_{ai}{}^{-L} \text{ and } y_{bi}{}^{-L} \begin{cases} \leq -0 & \text{for} 1=1,\cdots,N_i \\ =0 & \text{for} 1=N_i+1 \\ \geq 0 & \text{for} 1=N_i+2,\cdots,2N_i+1 \end{cases} \qquad (24)$$

Step 4:

Product inference engine, singleton fuzzyfier, and center average defuzzifier are selected to design the fuzzy controller.

2.2.6. Simulation results

The behaviour of the interconnected system outputs after implementing the fuzzy controllers with unity step function input are shown in Fig 12 and Fig: 13. It is clearly evident that the system becomes asymptotically stable by using the negative fuzzy feedback controller array.

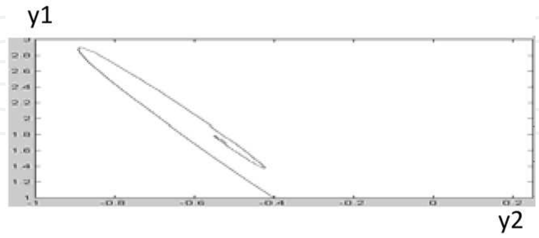

Figure 12. Outputs y1 against y2 y2

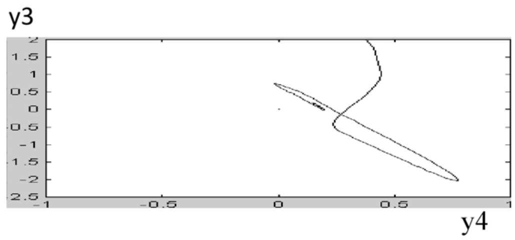

Figure 13. Outputs y3 against y4 y4

2.2.7. Performance of the proposed fuzzy feedback controller array

Now, we examine the effect of coupling matrices on the performance of fuzzy controlled interconnected system. Five additional cases with deferent coupling ranks are implemented. Fine tuning of membership functions was required to adjust their ranges. The following table summarizes the test cases:

Case No.	**A11,A2 2Norm**	**G12 Sparsty**	**G12 Norm**	**G21 Sparsty**	**G21 Norm**	**System Stability without controller**	**System Stability with controller**
1 (Fig 12, 13)	2.2529	3/25	0.2	3/25	1.8028	Unstable	Stable
2 (Fig. 14, 15)	2.2529	12/25	0.4712	3/25	0.1803	Unstable	Stable
3 (Fig. 16, 17)	2.2529	3/25	.2	12/25	0.5341	Unstable	Stable
4(Fig. 18, 19)	2.2529	1	3.0361	3/25	0.1803	Unstable	Stable
5 (Fig. 20, 21)	2.2529	3/25	.2	1	3.0364	Unstable	Stable
6 (Fig.22, 23)	2.2529	1	3.0361	1	3.0417	Unstable	Stable

Table 1. Results summary for 6 test cases.

The following figures illustrate the above test cases:

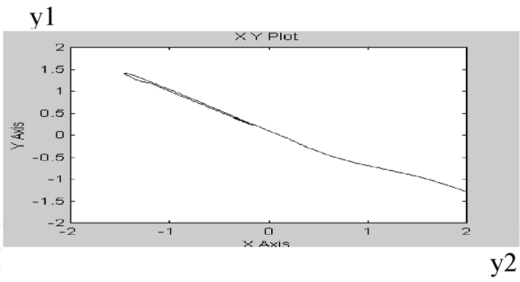

Figure 14. Case 2 Outputs y1 against y2

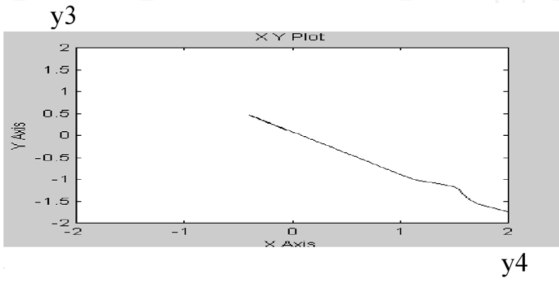

Figure 15. Case 2 Outputs y3 against y4

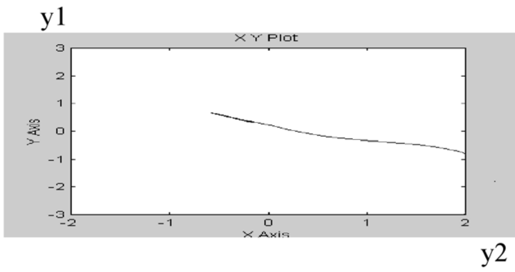

Figure 16. Case 3 Outputs y1 against y2

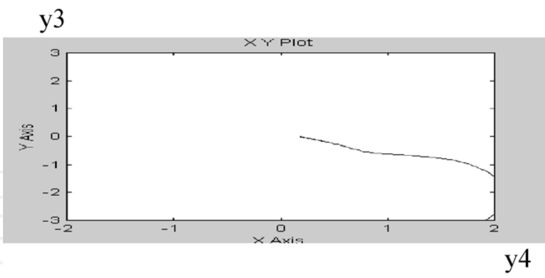

Figure 17. Case 3 Outputs y3 against y4

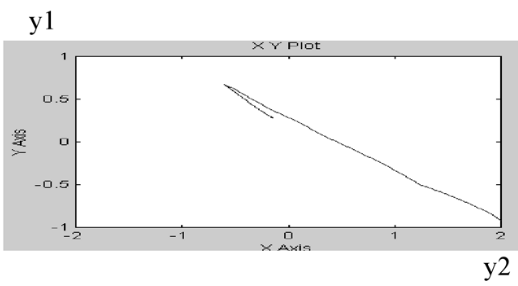

Figure 18. Case 4 Outputs y1 against y2

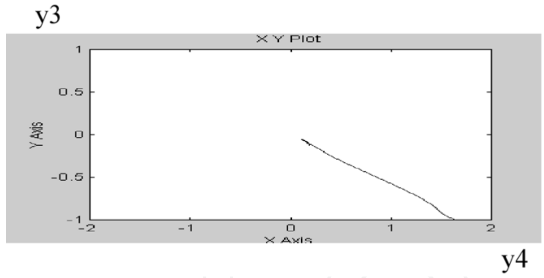

Figure 19. Case 4 Outputs y3 against y4

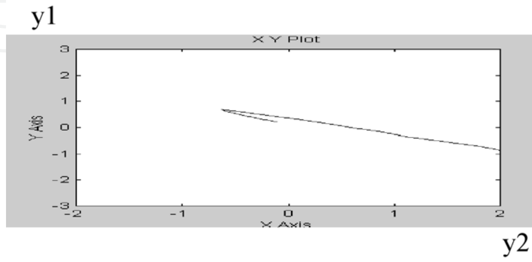

Figure 20. Case 5 Outputs y1 against y2

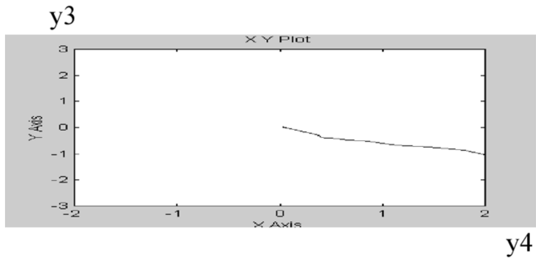

Figure 21. Case 5 Outputs y3 against y4

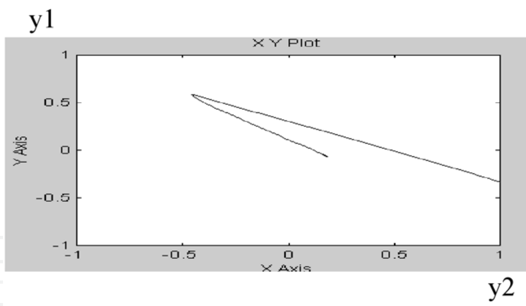

Figure 22. ase 6 Outputs y1 against y2

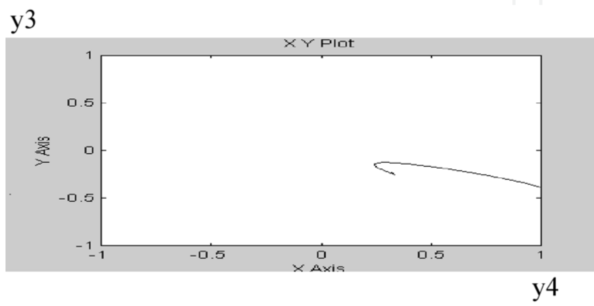

Figure 23. Case 6 Outputs y3 against y4

2.2.8. Discussion

This section has developed a new fuzzy control design approach to interconnected system. It has been shown the approach consists of two stages: In stage 1, a group of local state estimator has been constructed to generate the input-output database. Then an array of feedback controllers has been designed and implemented to guarantee the overall asymptotically system stability. Extensive simulation studies have been performed to support the developed design approach.

2.3. Power factor correction

This section presents the use of fuzzy logic technique to control the reactive power of a load and hence improve the power factor. A shunt compensator is used, which consists of a reactor in series with a phase controlled Thyristor bridge in parallel with a capacitor. The control composed of two independent fuzzy controllers, the Fuzzy Grouse Controller (FGC) and the Fuzzy Fine Controller (FFC). These fuzzy controllers are used to control the firing angle of the Thyristor Bridge until the source power factor reaches a desired value. Simulations for three different practical study cases are presented and the results show how the designed controller is fast and accurate.

2.3.1. Background

Power factor, nowadays, is an important issue. The over increasing utilization of power electronics in all kinds of industry applications and the severe standards requirements are pushing the research toward new solutions to keep the industrial power factor within certain ranges [26].

A mathematical formulation for the optimal reactive power control is discussed in [27]. Also, the optimized Fuzzy logic and digital PID controllers for a single phase power factor correction converter used in online UPS are demonstrated in [28, 29]. Parameters such as input membership functions, output membership functions, inference rules of fuzzy logic controller and proportional gain, integral gain and derivative PID controller are selected and optimized by genetic algorithms. In additional to that, the applications of a hybrid converter are implemented in [30]. The hybrid converter is basically a converter bridge with two GTOs. A control strategy based on learning is proposed. The learning structure is coded into Fuzzy conditional rules to train a neural network in manipulating the converter variables.

The common method of correction is by means of using static capacitors, whether connected in series or parallel. These are installed as a single unit or as a bank, to regulate the voltage and the reactive power flow at the point of connection. In shunt compensation arrangement, a reactor is connected in parallel with conventional capacitor compensation. The shunt reactor current can be varied via a phase-controlled thyristor bridge connected in series with the shunt reactor [31]. Changing the thyristor firing angle varies the amount. of the current flowing through the reactor. Thus, this thyristor controlled reactor acts as a variable reactor

[32]. By varying the firing angle, the total reactive power of the system can be controlled and hence the power factor of the system is improved. The use of fuzzy logic to derive a practical control scheme for a boost rectifier with reactive power factor correction was applied [33]. The control action is primarily derived from a set of linguistic rules used to generate a slow-varying DC signal to determine the PWM ramp function. The proposed technique uses lesser sensing elements than the classical rectifier. A new FACTS controller known as the Bootstrap variable inductance can emulate a variable positive and negative inductance [34]. The bootstrap variable inductance has a variety of FACTS applications such as series compensation of lines, fault current limiting, reactive-power control and load power factor improvement.

Here in this section, we shall focuses on the use of fuzzy logic sets to control the supply power factor. Unlike the conventional capacitive approach for power factor improvement in ac power system, the proposed control scheme has the advantage to avoid complexities associated with the non-linear mathematical modelling of switching converters. The proposed fuzzy logic controlling scheme consists of two controllers. The first controller (FGC) is designed to give the nearest desired value of the firing angle required to compensate for the source reactive power. However, the output correction of this controller is not efficiently accurate and hence, another correction step is needed. Thus, the second controller (FFC) checks the value of the source power factor and improves it above a pre-set desired value. The discussion includes the following:

- Illustration of the proposed control scheme.
- Description of the design steps of the power factor controller.
- Simulation of the proposed technique by testing it for three different study cases.

2.3.2. Fuzzy power factor controller

Figure 24 illustrates the block diagram for a single-phase variable load, with variable lag power factor, supplied by sinusoidal AC power source. Capacitor bank in parallel with inductance, controlled by single-phase full-wave circuit, are connected in parallel to the load in order to govern the total reactive power of the circuit. Fuzzy controller is designed to tune the firing angle of the single-phase full-wave circuit in order to adjust the voltage applied across the Inductance. By this way, the total source reactive power can be minimized to improve the source power factor. For three-phase circuits, one controller is dedicated for each phase. Here, we considered single-phase circuit for simplicity.

The structure of the controller contains two independent fuzzy controllers: Fuzzy Grouse Controller (FGC) and Fuzzy Fine Controller (FFC). FGC input is the load reactive power, the output of this controller gives the nearest value of the desired firing angle, which required to minimize the source power factor. FFC input is the source power factor. The output of FFC corrects the firing angle of the single-phase full-wave controller until the source power factor reaches or exceeds the pre-setted desired value.

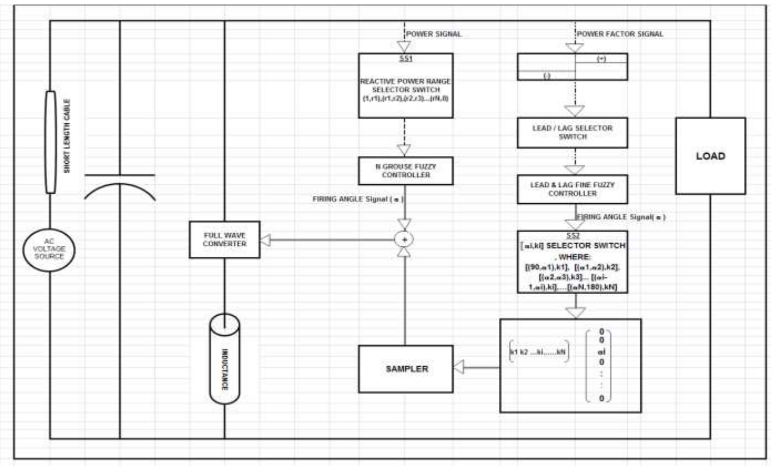

Figure 24. A detailed block diagram of the load, the fuzzy controllers, the source and the control scheme

The following procedures describe the steps of designing the power factor controller:

2.3.2.1. Elements sizing

The sizes of the 'Inductance' and the capacitance bank are selected such that their maximum available reactive power (in VAR) is equal to the maximum load reactive power (MLQ). Since the full source voltage is continuously applied on the capacitance bank (assuming the voltage drop across the short cable is negligible), then capacitance value 'C' of bank can be determined as follows:

$$C = \frac{\mathrm{MLQ}}{2 \times \pi \times f \times \mathrm{V}_{\mathrm{source}}^2} \quad \mathrm{Farad} \tag{25}$$

Where V_{source} is "source" r.m.s. voltage in Volt and f is "source" frequency in Hz.

However, this is not the case for the inductance since it is connected in series with a full wave controller. The existence of such controller will limit the available maximum reactive consumed by the inductance depending on the firing angle action of the thyristor bridge. Thus, the effect of the single-phase full-wave circuit is considered when determining the size of the inductance.

As listed in [35], the general formulas for the r.m.s value of current (I_{load}) and voltage (V_{load}) across a load, comprises of inductance in series with resistance, controlled by single-phase full-wave circuit. These formulas are given as follows:

$$\mathrm{I}_{Load} = \frac{\sqrt{2 \times} V_{source}}{z} [\frac{1}{\pi}\int_{\pi}^{\beta} \{\sin(\omega\, t - \theta) - \sin(\alpha - \theta) e^{(\mathrm{r}/_{1})(\alpha/\omega - \mathrm{t})}\} d\omega\, t]^{1/2} \tag{26}$$

$$\mathrm{V}_{\mathrm{Load}} = \frac{\sqrt{2 \times} \mathrm{V}_{\mathrm{source}}}{\mathrm{z}} [\frac{1}{\pi}\int_{\pi}^{\beta} \{\sin(\omega\, \mathrm{t} - \theta) - \sin(\alpha - \theta) \mathrm{e}^{(\mathrm{r}/_{1})(\alpha/\omega - \mathrm{t})}\} \mathrm{d}\omega\, \mathrm{t}]^{1/2} \tag{27}$$

Where:

$\omega = 2\pi f$ radian/second
α = Firing angle
β = Extinction angle (cut-off angle)
$\theta = \tan^{-1}(l/r)$
l = Load Inductance
r = Load Resistance
t = Time
z = Load impedance

Since the conducting angle $\delta = \beta - \alpha$ cannot exceed π, the firing angle α may not be less than θ and the control range of the firing angle is:

$$\pi \geq \alpha \geq \theta \tag{28}$$

For maximum available reactive power consumed by pure inductance MARP where r is ignored in the above equation 24 & 25), the maximum conducting angle is considered. Therefore, the value of the inductance can be calculated from the following equation assuming that $\alpha=\pi/2$ and $\beta=\pi$ (neglecting the impedance of the short Cable and assuming ideal thyristors):

$$\text{MARP} = \left(V_{load}\right) \times \left(I_{load}\right) \tag{29}$$

This MARP value must be equal to the maximum load reactive power MLQ for complete compensation. However, the two equations listed above are nonlinear and difficult to solve. Another simple procedure is needed when determining the size of the inductance L.

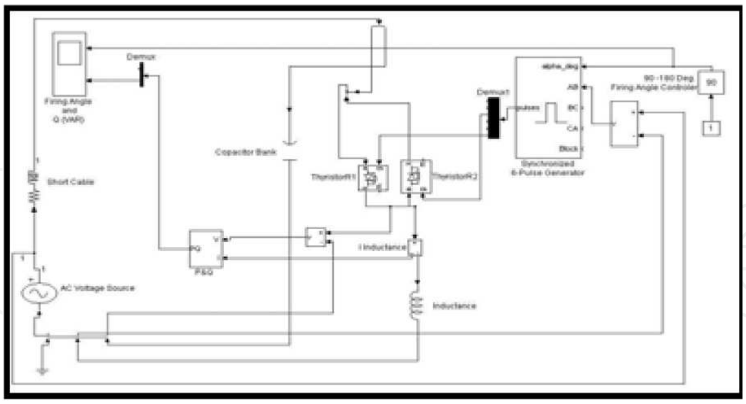

Figure 25. Simulink circuit used to determine and plot the ratio (Q_L/MLQ) verses firing angle (α)in the range from $\pi/2$ to π degree.

Thus, the value of the inductance can be found by a practical and fast method using Simulink tool [26]. Figure 25, illustrates the proposed model that been used. The model consists of an ac power source connected to a reactive power compensator controlled by a thyristor circuit. The procedure to find the value of the inductance L can be summarized by the following steps:

- Select an initial value for the inductance as L = 1 *(ω^2C)*
- Run the model and record the source VAR.
- If the source VAR equals zero, then stop the trials. If not, increase slightly the value of the inductance until the source VAR reaches the zero value. Then, this value of the source VAR will determine the desired value of the inductance.

2.3.2.2. Fuzzy Grouse Controller (FGC) design

After using the Simulink model shown in Figure 25, the inductance value is obtained from the iteration. Then, the same model is used again to find the ratio of (Q_L/MLQ) for a range of (α) starting from $\pi/2$ to π degree where (Q_L) is the Inductance reactive power at certain value of (π). This ratio (Q_L/MLQ) verses the firing angle (α) is then plotted. Typical curve is shown in Figure 26.

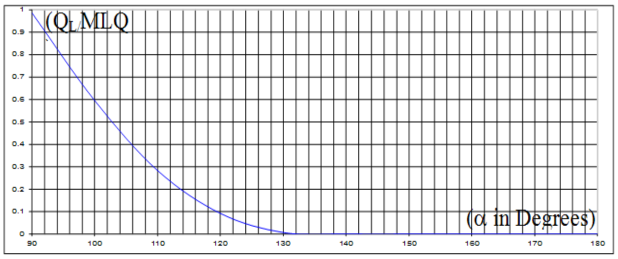

Figure 26. Typical curve for (Q_L/MLQ) verses firing angle (α)

After that, the resultant nonlinear curve is divided to N sections where each nonlinear section is approximated by the nearest linear section. Thus, N Gross Fuzzy controllers (FGC) are built, one FGC for each section, such that the input of each controller is equal to 1-(Q_{Load}/(MLQ), where (Q_{Load}) is the load reactive power. The output of the FGC is the firing angle (α), which results in (Q_L) approximately equal to MLQ minus Q_{Load}. The accuracy of the resultant (Q_L) depends on the curve linearization.

In order to design each FGC, let the full range of the input fuzzy membership function FGCMF(in)[a] for each controller is set to the (Q_L/MLQ) limits of the respective linearzed section, and the range of the output fuzzy membership function FGCMF(out)[b] for each controller is set to the (α) limits of the respective linearzed section. For example, in Case 3 (as will be explained later into details), the first controller is designed to take an action in case of (QL/MLQ) ratio reaches a value between rl=0.95 and 1and, the output firing angle of this controller shall take a value between 90 degree and α_1 = 100 degree. However, the second controller is designed to take an action in case of (QL/MLQ) ratio reaches a value between r2 = 0.175 and rl = 0.950 and, the output firing angle of this controller shall take a value between α_1 = 100 degree and α_2 = 105degree, and so on.

The resultant output of each fuzzy controller can be obtained based on the respective linearzed section using the following functions for fuzzy implication process:

- Mamdany engine.
- Triangle type for Membership functions.
- Product for And.
- Max for Or.

- Proportional for Aggregation.
- Largest of Maximum for Defuzzification.
- Fuzzy rule : IF is $MF(in)^a$ THEN (α) is $MF(out)^b$

where,

a = 1,2, ... F (fuzzy membership function number)
b = F-a+l(fuzzy membership function number)
a and b are fuzzy membership function numbers
F is the number of the fuzzy membership function.

Simulink automatic switching system SS 1 as shown in Figure 24 is designed to check the active range of (Q_L/MLQ) in order to select the proper FGC based on that value of (Q_L/MLQ) ratio.

2.3.2.3. Fuzzy Fine Controller (FFC) design

Since the FGC output is not accurate due to the linearization process, FFC is designed to tune the firing g angle in order to achieve the desired power factor.

Two fuzzy control1ers are used along with automatic switching system to select the proper controller based on the power factor type (Lead or Lag), which is determined from the source VAR sign (+ or -) as shown in Figure 24.

The input of each FFC controller is the source power factor (PF) and the output is the corrective firing angle (M), which is required to fine tune the FGC output. Since the power factor value varies between zero and one, then the range of each FPC input membership function $FFCMF(in)^a$ is [0, 1].

The output membership function of each FFC is $FFCMF(out\text{-}Lag)^a$ for lagging input and $FFCMF(out\text{-}Lead)^a$ for leading input and, the magnitude of the firing angle range for the first linearzed section (α_1) is considered as a base to scale the FFC output as given hereinafter with the fact that any other section can be selected as the base. Also, [0, $\Delta\alpha_1$] and [-$\Delta\alpha_1$, 0] are assigned to $FFCMF(out\text{-}Lag)^b$ and $FFCMF(out\text{-}Lead)^b$ respectively. In addition to that, N multiplier factors ($k_N = \Delta\alpha_N, / \alpha_1$) are used to scale the FFC output in order to match the magnitude of the firing angle range of the respective linearzed section ($\Delta\alpha_N$). By this method, less number of FFC's are used.

Another Simulink automatic switching system SS2 as shown in Figure 24 synchronized with SS 1 is designed to check the active range of (Q_L/MLQ) in order to select the proper multiplier factor (K_N). The fuzzy implication process functions used for FGC design are used for each FFC design as well, but with the following fuzzy rules:

$$\text{IF } (\text{PF}) \text{is FFCMF } (\text{in})^a \text{ THEN}(\alpha_\Delta) \text{ is FFCMF } (\text{out Lag})^a \tag{30}$$

$$\text{IF } (\text{PF}) \text{is FFCMF } (\text{in})^a \text{ THEN}(\alpha_\Delta) \text{ is FFCMF } (\text{out Lead})^a \tag{31}$$

2.3.2.4. Discrete control signal design

Simulink Sum Block is used to add the output of GFC to the output of FFC. Sampler system shown in Figure 24 is designed to convert the resultant analog control signal to discrete signal. The sampling time is selected to be greater than the system time constant. The discrete signal is connected to the input for the synchronized pulse generator to control the thyristor firing angle. Accordingly, the network var and the source power factor are controlled.

2.3.3. Case study

The Simulink circuit shown in Figure 24 is used as a base to study three 'test' cases. These cases are assigned to check the capability of the controller to operate within a considerable variation of power factor values at different loading and voltage level.

			Case 1	**Case 2**	**Case 3**
Source Voltage (Volt)			**120**	**480**	**4160**
	Stage 1	P1 (kW)	2	40	40
		Q1(kVAR)	3.197	142.857	142.857
	Stage 2	P2 (kW)	12	200	240
Load Stages		Q2 (kVAR)	12.789	571.429	428.571
	Stage 3	P3(kW)	32	1200	1240
		Q3 (kVAR)	22.38	1000	1000
	Stage 4	P4 (kW)	42	2240	2280
		Q4 (kVAR)	0	0	0
MLQ (MVAR)			0.02238	1	1
F (Number of fuzzy membership functions)			7	7	7
k1			1	1	1
k2			2.8	0.95	0.5
k3			0.44	1	2.3
k4			5.7	4.5	5.3
r1			0.64	0.52	0.95
r2			0.28	0.21	0.2
r3			0.03	0.02	0.04
ALPHA1 (DEGREE)			99	102	100
ALPHA2 (DEGREE)			124	113.5	105
ALPHA3 (DEGREE)			128	125.5	128
N (Number of sections)			4	4	4

Table 2. Circuit data and parameters for the test cases

2.3.4. Test cases data

Each test case consists of four load stages. The load stages are selected such that the power factor varies from 0.3 to 1.0 lag. However, for practical cases, the power factor varies between 0.6 to 0.8 and thus the proposed wide range of power factor tested here is to demonstrate the capability of the designed controller. Table 2 summaries the circuit parameters for three voltage levels 120. 480 and 4160 Volts respectively. Figures 27-29 illustrate the linearization process for each case.

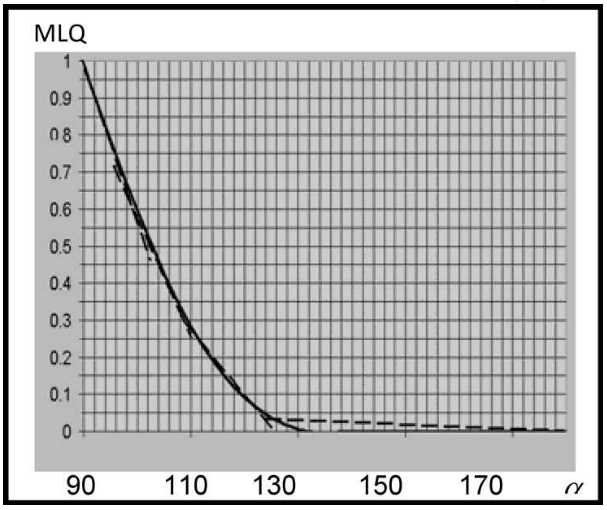

Figure 27. Linearization results for case1.

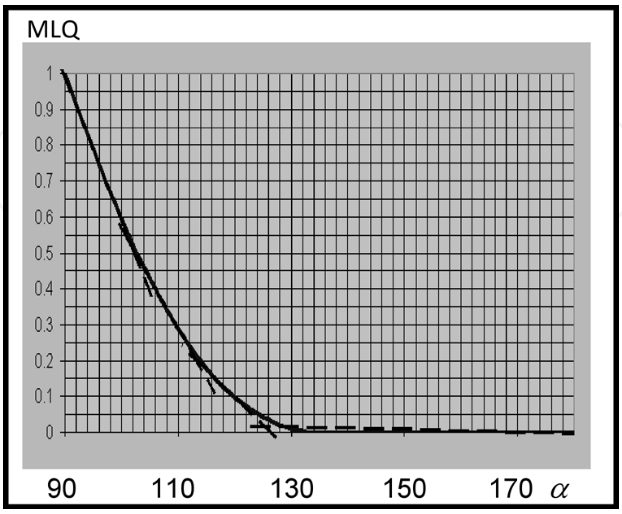

Figure 28. Linearization results for case 2

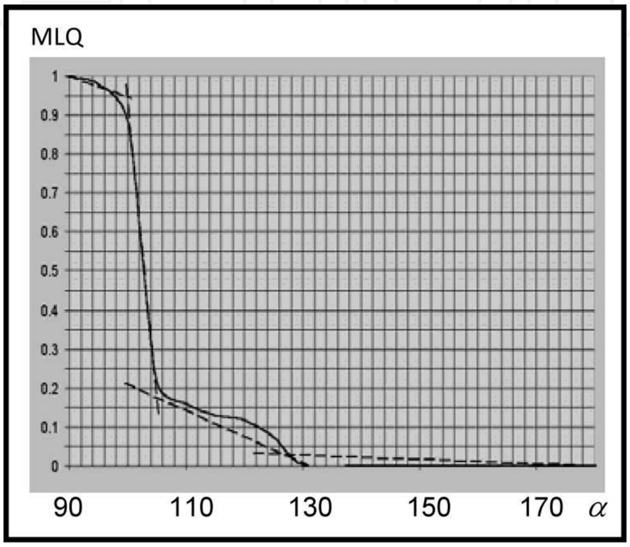

Figure 29. Linearization results for case 3

2.3.5. Results

The controller is adjusted to correct the power factor of the test cases to a value greater than a desired value of 0.97. This value is the pre-set value and it can be any chosen practical value. Figures 30 -32 illustrate the results for cases 1-3 respectively. These figures show the variation of the load active and reactive power with respect to time for each case. The response of the controller during the test period represented by the firing angle is also shown. In addition to that, source and load power factor values are plotted to check the response time of the controller and its accuracy.

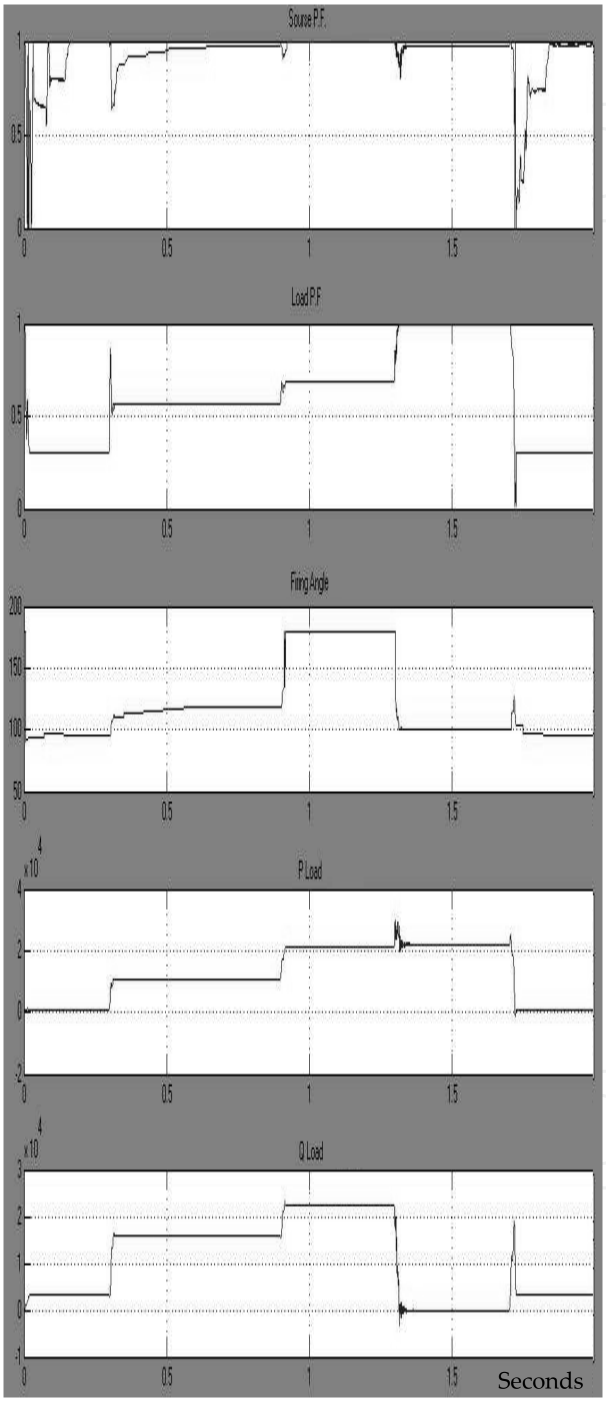

Figure 30. Results of test case 1.

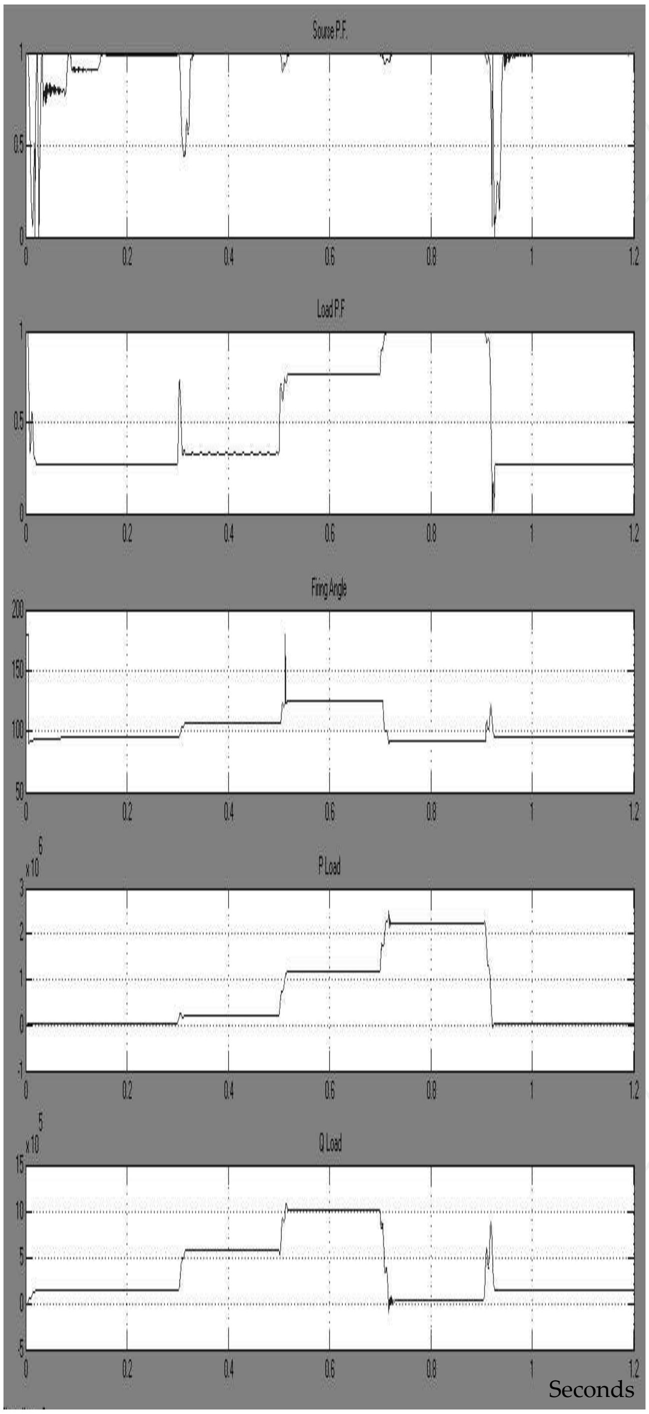

Figure 31. Results of test case 2.

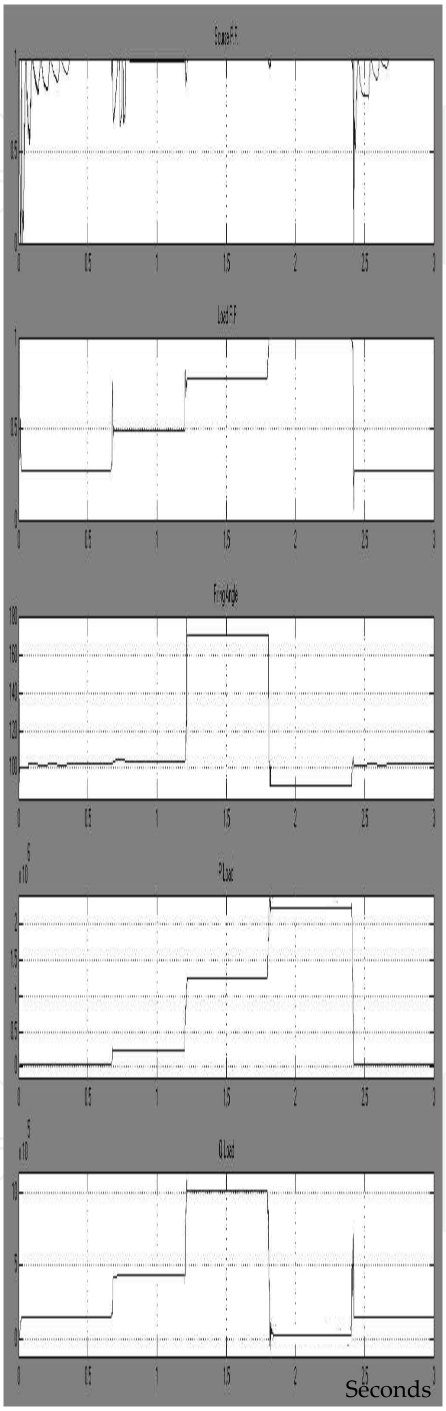

Figure 32. Results of test case 3.

2.3.6. Discussion

The test results for the three cases show clearly how efficient is the controller. Even when the load reactive power is very small at both high and low power factor, the controller was successful in reaching an accurate level. During the stage where the load power factor is greater than 0.97 and, hence no need for capacitor compensation, the controller will check the source power factor at the beginning of that stage and if it drops below 0. 97, it will take an action in order to eliminate the compensation added in the previous stage. That is why the controller took an action as shown in Figure 30 for the fourth load stage of case no. 1 where the source power factor drops below 0.97. However, if the source power factor stays above the pre-set power factor value of 0.97 during the load stage where the load power factor is greater than 0.97, then no action will be taken as shown in Figure 32 for the fourth load stage of case no. 3. The time required for the controller to improve the power factor in all three cases is relatively short compared with practical applications. In real cases, the power factor does remain unchanged for relatively longer time. The maximum time for power factor correction was 0.35 second recorded in test case no.1. Overall, the graphs show that the controller works satisfactory under different load conditions and when there is no need for capacitor compensation.

As mentioned before, power factor correction is really an important issue. The designed controller presented in this section shows an efficient, fast and accurate technique in reactive power control. As seen from the overall structure of the controller, it is applicable for lagging power factor loads. Practically, this is almost true but not always where at rare occasions the power factor of the total load is leading not lagging. This will bring the attention towards generalizing the presented controller such that it will work for both cases. Several issues are also need to be considered in the future such as the dynamics of motors. As known that most connected loads are motors which really necessitate testing this controller under these circumstances. From the test results, it was seen that the speed of the controller depends on the system time constant and hence, a time delay is needed to assure that thc dynamics of the motors reach its equilibrium. Other issues related to Thyristors such as the harmonics are a1so need to be taken care by describing a harmonics filter. In addition to that, protection devices such as relays need to be checked during the controller action. Finally, the work presented was based on a single phase and it can be extended for three phase system.

3. Trending and prediction

Most of the more advanced prediction techniques can be subdivided into two separate tasks. In a first step, the modelling step, the algorithm uses a set of training data to identify a model of a process, from which the training data could have been obtained. In a second step, the simulation step, the algorithm uses the previously identified model to make predictions outside the training data set. The modelling algorithm can either attempt to identify the true structure of the system, from which the training data were obtained, or it can content itself with identifying any process able to explain the training data set. In the former case, we talk about a deep model, whereas models in the latter category are referred to as shallow models.

The identified model can be either a quantitative or a qualitative model. A quantitative model operates on the measurement data directly, whereas a qualitative model first discretizes the measurement data, and then reasons about the discrete classes only. Also the model can be either a parametric model or a nonparametric model. A parametric model maps the knowledge contained in the training data set onto a set of model parameters. During the simulation phase, the training data are no longer needed, since the information contained in them is now stored in the parameter values. A non-parametric model only classifies the training data during the modelling phase, and refers back to these classified training data during the simulation phase.

Fuzzy logic are used now a day in many application for diagnostic, prediction forecast and understanding the behaviour of very nonlinear systems such as marketing, electrical load forecast, work load analysis, technical analysis etc…

In this chapter Section 2.1, we shall introduce an important algorithm for classifying "clustering" the data based on fuzzy logic. Then two new fuzzy trending and prediction application shall be discussed. In Section 2.2 Accident rates Estimation Modelling Based on Human Factors shall be introduces, and in the next section 2.3, Fault Location in Distribution Networks shall be introduced.

3.1. Clustering algorithm and validity criteria

Clustering attempts to assess the relationships among patterns of the data set by organizing the patterns into groups or clusters such that patterns within a cluster are more similar to each other than are patterns belonging to different clusters. Many algorithms for hard and fuzzy clustering have been developed to accomplish this[42]. An intimately related important issue is the cluster validity, which deals with the significance of the structure imposed by a clustering method [43].

For fuzzy sets, the following definitions are recalled from [36]:

a. A fuzzy set in a universe discourse U is characterized by a membership function $\mu_A(x)$ that takes values in the interval [0,1].
b. Let $X=\{x_1,\ldots,x_n\}$ be any set, V_{cn} be the set of real c×n matrices $U=[\mu_{ij}]$, c, i, j be integer numbers with $2 \le c \le n$, $1 \le i \le c$ and $1 \le j \le n$ .Then the fuzzy partition matrix for X is the set $M_{fc} = \{U \in V_{cn} \mid \mu_{ij} \in [0,1]\}$ (32)

Such that

$$\sum_i \mu_{ij} = 1, \forall_j, 1 \le j \le n. \tag{33}$$

An α-cut of fuzzy set A is a crisp set $A\alpha$ that contains all the elements in U that have membership value in A greater thanα, that is

$$A_\alpha = \{x \in U \mid \mu_A(x) \geq \alpha\} \tag{34}$$

c. Defuzzification is defined as a mapping from fuzzy set B` in $V \subset R$ to crisp point $y^* \in V$. Conceptually, the task of the defuzzification is to specify a point in V that best represents the fuzzy set B`.

The following three criteria should be considered in choosing the defuzification method:

- Plausibility: The point y^* should represent B` from an intuitive point of view.
- Computational simplicity.
- Continuity: A small Change in B` should not result in a large change in y^*.

3.1.1. Fuzzy C-Means Clustering Algorithm(FCM)

The fuzzy c-means (FCM) clustering algorithm is the fuzzy equivalent of the nearest hard clustering algorithm [43,44], which minimizes the following objective function with respect to fuzzy membership μ_{ij}, and cluster centroid V_i.

$$J_m = \sum_I^c \sum_j^n (\mu_{ij})^f \mid\mid \left(X_j, V_i \right) \mid\mid^2 \tag{35}$$

where $X = [X_1, \ldots, X_n]^t$ is a vector representing the data, c is the number of clusters, n is the number of data points and f is a fuzziness index (greater than 1)

The FCM algorithm is executed by the following steps:

a. Initialize memberships μ_{ij} of X_j belonging to cluster i such that

$$\sum_j (\mu_{ij}) = 1 \tag{36}$$

b. Compute the fuzzy centroid V_i from i=1 to i=c using

$$V_i = \frac{\sum_j (\mu_{ij})^m \times X_j}{\sum_j (\mu_{ij})^m} \tag{37}$$

c. Update the fuzzy memberships μ_{ij} using

$$\mu_{ij} = \frac{(\mid\mid (X_j, V_i) \mid\mid)^{(-2/(m-1))}}{\sum_j (\mid\mid (X_j, V_i) \mid\mid)^{(-2/(m-1))}} \tag{38}$$

d. Repeat steps 2 and 3 until the value of J_m is no longer decreasing.

The FCM always converges to strict local minimum of Jm starting from an initial guess of μ_{ij}, but different choices of initial μ_{ij} might lead to local minima.

3.1.2. Cluster validity

The quality of a clustering is indicated by how closely the data points are associated to the cluster centers, and it is the membership functions, which measure the level of association or classification. If the value of one of the membership is significantly larger than the others for a particular data point, then that point is identified as being a part of the subset of the data represented by the corresponding cluster center. But, each data point has c memberships; so, it is desirable to summarize the information contained in the memberships by a single number, which indicates how well the data point is classified by the clustering. This can be done in a variety of ways; for example, for the data point X_j with memberships $\{\mu_{ij}, ..., \mu_{cj}\}$, one could use any of the following:

$$\text{Index1} = \sum_i (\mu_{ij})^2 \quad (39)$$

$$\text{Index2} = \sum_i \mu_{ij} \log(\mu_{ij}) \quad (40)$$

$$\text{Index3} = \max_i (\mu_{ij}) \quad (41)$$

$$\text{Index4} = \min_i (\mu_{ij}) / \max_i (\mu_{ij}) \quad (42)$$

In fact, theses four indices of these are used as measure of the quality of clustering and are the basis for the *validity functional*, *partition coefficient*, *classification entropy, and proportion exponent*, respectively.

To illustrate the use of validity functional, we shall focus on the partition coefficient technique because of its simplicity. It is based on using $S_j = \Sigma_i (\mu_{ij})^2$ as a measure of how well the jth data point has been classified. This is a reasonable indicator because the closer a data point is to a cluster center, the closer S_j is to 1, the maximum value it could have. Conversely, the further away the kth point is from all the cluster centers the closer the value of S_j is to 1/c, the minimum possible value. The partition coefficient is then the average over the data set of the S_j's. In particular, for a data set $X=\{x_1,\ldots,x_i\}$ and a specific choice of c and m one obtains the output of fuzzy c-means and computes the partition coefficient (PC) by $PC=\Sigma_j(\Sigma_i(\mu_{ij})^2/n$. The closer this value is to one the better the data are classified. So, in theory, one computes PC for the outputs of a variety of values of c and m selects the best clustering as the one corresponding to the highest partition coefficient [44,45].

3.2. Accident rates estimation modeling based on human factors using fuzzy c-mean clustering techniques

Several individual books [37] and projects shed light on worker accident causation. One study on the Bonneville Dam project, reported that seven times the number of work accidents that had occurred on this project were due to unsafe employee actions rather than to unsafe site conditions. In addition, this study found that the negative attitude of the workers toward safety was a major factor in accident occurrence.

In [38]. Many organizations spend a lot of time and effort trying to improve safety. As well as addressing technical and hardware issues, many conduct safety management system audits to discover deviations from the performance standards set in their Health & Safety

Policies. Line management is encouraged to conduct regular inspections of the workplace and employees are trained to behave safely and are given the appropriate protective equipment. The impact of such initiatives could be seen in the overall downward trend in accident statistics from 1990 to 1998/99. After 2000, accident statistics started rising in many UK industrial sectors. In the Quarry Industry, for example, there has been a 60% rise in the number of fatalities.

Another study by Stanford University [39] indicated that risk taking is often a normal part of human psychology. We sometimes drive too fast or take chances we should not. Risk which is taken on the job site, however, can be fatal. This study found that many workers believe that taking unnecessary risks is an accepted part of the job process. This risk acceptance attitude leads to carelessness and accidents. The results of the Stanford study show that workers who are likely to have lost-time accidents share similar characteristics. These workers have a negative attitude toward doing their jobs safely, and they accept unnecessary risk and, therefore, do not work safely. Taking unnecessary risks and adopting a poor safety attitude simply makes workers more prone to accident occurrences. The conclusion of the Stanford study clearly supports the contention that employee actions and attitudes can affect the number and type of workplace accidents. Employers can and do address this attitude of risk taking through safety education, safety rules, and training programs. However, no employer can supervise each employee every minute of the work day.

In [40], the paper focuses on the development and representation of linguistic variables to model risk levels subjectively. These variables are then quantified using fuzzy set theory. In this paper the development of two safety evaluation frameworks, using fuzzy logic approaches for maritime engineering safety based decision support in the concept design stage are presented. An example is used to illustrate and compare the proposed approaches. The paper also suggests that future risk analysis in maritime engineering applications may take full advantages of fuzzy logic approaches to complement existing ones.

The field of fuzzy systems has been making rapid progress over the past decade [36]. There are two kinds of justification for fuzzy systems to be used to achieve our objective:

a. The problem is too complicated for precise description to be obtained, therefore approximation, or fuzziness, must be introduced in order to be a reasonable and net traceable model.
b. As we move into the information era, knowledge is becoming increasingly important and the need for a theory to formulate human knowledge in a systematic manner becomes the norm not the exception.

But as a general principle, a good engineering theory should be capable of making use of all the available information effectively. For many practical systems, important information comes from two sources: one source is from human experts who describe their knowledge about the system in natural languages; the other is sensory measurements or mathematical models that are derived from to physical laws.

An important task, therefore, is to combine these two types of information into system designs. Therefore, the key question is how to transform human knowledge base into a mathematical formula or model. Essentially, what a fuzzy system does is to perform this transformation in a systematic way.

In this part of Section 2, we attempt to use a completely different approach to analyze - accidents. A model shall be developed for data collected from an accident rate questionnaire filled-in by laborers working for a reputable construction company. This questionnaire was designed to include information about human factors, as well as other factors such as work type, managerial factors, training, physical factors and the historical accident rate for each labor during his period of employment in this particular construction company, and his experience during his career life time. The collected data shall be split into a training set for model construction and a test for model verification. The training information shall be classified into a number of groups or clusters, the centroids of these clusters were subsequently used to generate a set of rules to develop a fuzzy engine, which can then predict and forecast the rate of accidents. The test cases shall be used to verify and validate the developed model. Discussion on the results obtained from using fuzzy logic techniques shall be carried out.

3.2.1. Data organization

Construction sites are very dynamic and complex by nature, creating the potential for hazards that change constantly. So, what was safe yesterday may no longer be safe today. Thus, safety precautions should be followed and controlled. Unsafe working conditions and accidents are usually warning signs that something is wrong and has to be rectified.

Different government authorities measure safety at construction sites [41], however co-ordination and sharing of information with each other is still lacking. In addition, the data available on construction site accidents are neither accurate nor complete, due to the absence of a reliable accident reporting and recording system. Incomplete records are due to the poor accident investigation that may be a result of:

- Reluctance of reporters to assert authority.
- Inexperienced and untrained investigators
- Narrow interpretation
- Judgmental behavior.
- Incomplete or erroneous conclusions.
- Delays in accident investigations.

For these reasons we endeavored to avoid the normal way of doing the job, and instead, we focused on the laborer, himself, and his accident rates during his years of work experience as an expert source of data. We have tried to design the questionnaire in such a way as to serve our purpose of analyzing the data, and selected the interview method to get the maximum precise data possible.

3.2.1.1. Questionnaire design

In the design of questionnaire (Appendix) we have selected some certain features of human nature that, we believe, have a great potential on the accident causation in the local market [41]. The first page of the questionnaire concentrated on the personal information of the workers: i.e. 'height', 'weight', 'optical status', 'hearing ability', 'general health', 'education' and 'adherence to safety rules'. In this part we used some linguistic evaluations like 'high', 'low', 'fair', 'good', 'medium' etc., and in some others we have used numerical evaluations like in height, weight, as well as education. Since the objective here is to create a fuzzy model, high accuracy is not important and we considered that the respondents from the same field made the same judgments.

The second page was designed to concentrate on the work information: 'overtime work', 'experience', 'work nature', 'work type', 'hazardous level', 'needs for safety-gears', 'work location' and 'level of boredom'. Again, we have used some linguistic evaluations as well as numerical evaluations. We also concentrated on the managerial factors: 'salary received on time', 'level of training' 'importance' and level of importance placed on safety', with only linguistic evaluations.

The third page was a mix of both external factors: 'noise', 'live with family' and 'communication 'language', and accident history focusing on the number of accidents the laborer has faced during his work in the local construction market, which was the most important data that we needed to develop our model. The severity of accidents has not been taken into account since it is not considered a factor influencing the accident rate.

The cases obtained for this study were collected from three different construction companies selected to represent the local market. We have tried to select the cases from different ranks of the workforce, from higher levels to the lower levels to be able to study the different accident level cases that serve the purpose as well as adding versatility and diversity to this work.

3.2.1.2. The response

From the original cases that we collected on 95 people, we included only 76 cases and excluded 19 cases, which were incomplete. This has produced a very high response rate that reached 82.1%, which is relatively high, especially as the questionnaire is lengthy and a little bit complicated. More cases could have been obtained. However, since the aim of this study was to develop a model for accidents, the number of cases is not set a priority. Rather, the cases are accumulated and the algorithms are stopped when a cluster validity criterion is satisfied thereby yielding the optimum number of clusters.

3.2.1.3. Limitations

Limitations in this study should be noted. One of the limitations is that we did not include any specific information related to the accident consequences. Another limitation is that this study was made only on males and no female cases were studied, which makes it specific only to one sex.

3.2.1.4. The feature matrix

The feature matrix (FM) is the most important part of our work in this section , since by using this matrix we have been able to convert the linguistic variables into numerical variables. Thus, we can deal easily with practical cases and reduce the required operations of processing the output.

The columns of the FM matrix represent the feature variables which we obtained from the questionnaire. The rows of the matrix represent the different cases of laborers that we selected for interviews. Thus, for each case in the matrix we mapped the linguistic meanings into numbers according to weights we have proposed. For example, in case labelled (S1), the feature weight 1 (FW1) represents the rate of accidents per year of experience, which is the actual representation of the accident rates. FW2 represents the ratio between weight and height (specific weight). FW3 represents optical status and FW4 represents hearing ability. These feature weights are scaled on a scale of five from 1 to 5, to represent the linguistic variables. Therefore, 1 means `very bad`, 2 means `bad`, 3 means `medium`, 4 means `good` and 5 means `very good`. All the other variables are dealt in the same way until the matrix was generated. A sample of the feature matrix is shown in Table3.

Feature / Case No	Accidents/ experience	Weight/ Height	Optical status	Hearing Ability	General Health	Adherence to Safety	Education	Overtime work
S1	1/12	71/160	6/18	5	5	4	5	2
S2	5/12	77/ 170	6/60	5	4	3	5	3
S3	1/21	90/175	6/6	4	5	5	5	5
S4	0/8	54/165	6/60	4	5	2	5	20
S5	6/3.5	68/187	6/36	3	4	3	5	0
S6	10/11	85/177	6/6	4	4	3	5	10
S7	2/19	76/173	6/60	4	5	5	5	14
S8	18/25	72/170	6/18	3	4	4	4	4
S9	45/14	80/176	6/6	4	4	3	4	8
S10	3/20	81/174	6/6	4	4	5	4	1

Table 3. Sample of feature matrix illustrates the weight of some features for the first 10 cases

3.2.2. Modelling

In this stage, FCM techniques will be implemented on the feature matrix after normalizing the data, based on column maximum values for ease and as being more indicative, then deciding the optimum number of clusters, by applying cluster validity techniques. The centroides for these optimum clusters are considered perfect models represent the feature matrix.

In order to obtain the models, the following steps have been implemented:

- Each column in the feature matrix is normalized by dividing all the numbers in this column by the maximum number of the absolute values of all the numbers in the said column.
- Cluster validity study is implemented to determine the optimum number of clusters for the normalized data.
- FCM technique is implemented to determine the centroids matrix of the selected number of clusters.

MATLAB fuzzy toolbox has been used to implement the above three steps [46].

3.2.2.1. Clustering results and discussions

The results can be summarized as follows:

a. The optimum number of cluster (twelve) is determined by implementing cluster validity technique. The result is illustrated in Figure 33 which gives the relation between the number of clusters and the corresponding error where:

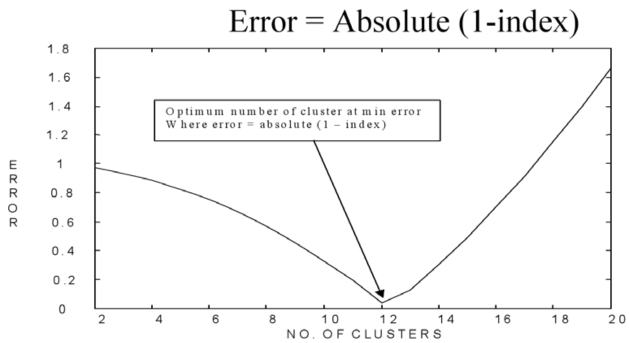

Figure 33. Relation between number of clusters and the corresponding error

b. Table 9 (Appendix) illustrates the centroide matrix for the optimum number of clusters (twelve), where FW(j) stands for feature weight described in Table 10 (Appendix).

3.2.2.2. Scaling of data

In order to reduce the error in the estimation of the membership functions ranges (e.g. the estimated range of FW5 was from 1 to 5, while from centroide matrix the range for the same feature is found to be from 3.750 to 4.9953) each feature vector element is scaled according to the following formula:

$$X_{scaled} = X_i - X_{min} / \left(X_{max} - X_{min}\right) \quad (43)$$

Where:

X_i = Vector element
X_{min} = Min. Vector element
X_{max} = Max. Vector element

3.2.2.3. Model development

By comparing each row of the centroids matrix with the contents of the questionnaire after scaling, one can infer the structure of the respective model, for example maximum and minimum rate of accident as illustrated in Table 11 (Appendix). From structure, following features can be extracted:

a. Labours in this construction company can be classified into 12 models.
b. The expected range of accident rate in company varies from 0.1581 to 2.8894 accidents per year.
c. By comparing the above two extreme models, one can easily discover that receiving salary on time has no effective impact on accident rate.
d. The highest rate of accidents occurs to non-local workers (Live without their family most of the time).
e. The twelve models obtained above shall be utilized later as fuzzy rules representing the this local construction company to predict the rate of accident for any person working on construction field.

3.2.3. Accident rate prediction

Now, fuzzy logic techniques will be implemented using the models obtained in Section 2.2.2, as perfect fuzzy rules, to predict the accident rate for any laborer who works in the construction field. The following flow chart (Figure 34) describes the fuzzy accident prediction system:

The models obtained from the fuzzy c -means the clustering process has been considered as very good and suitable fuzzy rules that govern the relation between the laborers in construction field and the expected annual rate of accident.

The beauty of using this type of clustering is not only to achieve the required models, but also these models are fuzzy, and can be geared in the fuzzy engine.

In order to fuzzify the model variables, a suitable number of Gauss functions (linguistic variable) is selected for each linguistic value so that any rule must fire all the linguistic values and the rules are given as follows [36]:

$$\text{IF}\left(\text{FW1 is } \text{mf}_a{}^1\right) \text{ and } \left(\text{FW2 is } \text{mf}_b{}^2\right) \text{ and} \ldots \left(\text{FW22 is } \text{mf}_v{}^{22}\right) \text{ THEN } \left(\text{FW23 is } \text{mf}_w{}^{23}\right) \quad (44)$$

Where,

FW(1to22) : input linguistic variable
FW23 : output linguistic variable
mf $_{a,b\,..w}$: semantic rule
a,b ..w: integer number from 1 to 5

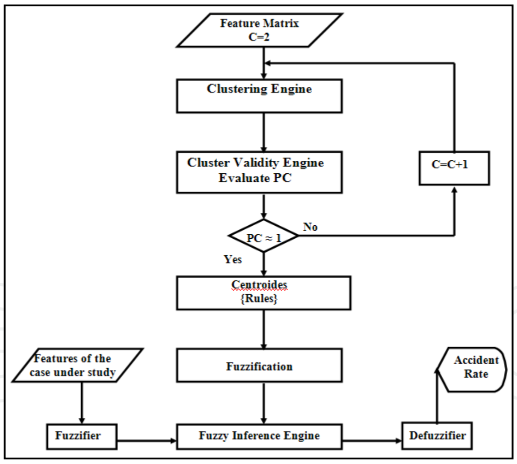

Figure 34. Fuzzy Accident Prediction Flowchart

Mamdani inference engine with centroid defuzzification and proportional aggregation is used in the construction of the fuzzy system. MATLAB Fuzzy Toolbox has been used to implement the required fuzzy prediction system. Eight cases have been tested and the results are given in hereinafter.

3.2.3.1. Relevant results

a. Eight additional random cases have been chosen from a local construction company. Features, actual accident rate and output of fuzzy prediction system for each test case are given in Table 12 (Appendix). The standard deviation between the actual accident rate and the predicted accident rate for each test case is calculated then the average standard deviation is obtained in order to determine the validity of the model. The results are shown as follows in Table 4:

Case Number	Standard Deviation
Case#1	0.3536
Case#2	0.2828
Case#3	0.4243
Case#4	0.7071
Case#5	01414
Case#6	0.1414
Case#7	0.2121
Case#8	0.0318
Average	0.2868

Table 4. Standard deviation results for the test cases

b. In (Appendix), Figure 37 shows the output of the prediction system for a case that fires all the linguistic values at the middle. It is observed from this result that the laborers with `average` personal information, `average` work condition, `average` managerial condition and `average` external effects are exposed to `average` annual accident rate.

c. Figure 38(Appendix) correlates the laborers general health and specific weight with their annual accident rate considering all other factors are `average`. It is clear that the annual accident rate increases with the significant increase of the specific weight and significant poorness of the general health.
d. In Figure 39 (Appendix), the laborers educational level and safety adherence are plotted against their annual accident rate considering all other factors are `average`. It is noticed from this illustration that the laborers with the two educational level extremes are exposed to accidents more than the `average` educational level laborers.
e. Figure 40 (Appendix) correlates the laborers optical status and hearing ability with their annual accident rate considering all other factors to be `average`. It is clear that the annual accident rate increases with the significant poorness of the optical status and hearing ability.
f. From the last plot (Figure 41 - Appendix), it is clear that if the company is not keen on the level of safety, the annual accident rate will be increased, considering all other factors are `average`. In addition, it is noticeable from the figure that the tasks that are considered to be dangerous and need safety-gear are a source of accidents.

3.2.4. Discussion

The main objective of in this example to generate a human model which reflects the interaction between human factors in addition to other factors such as managerial factors, accident information, and work information, using fuzzy clustering techniques. Secondly, to predict annual rate of accident for any sample of workers by applying fuzzy logic techniques. Some of the important results obtained can be summarized as follows:

a. Fuzzy clustering techniques can be used to build a model that characterizes the different features of workers in local construction field against their rate of accidents.
b. The model obtained from clustering is considered as rules to be used in a fuzzy logic engine to predict the rate of accidents for any worker in the construction field.
c. For any specific case, 231 correlations (between any two features and the rate of accidents) can be done via the fuzzy engine.
d. Optimum training to improve the safety attitude for certain laborer with minimum cost can be estimated by analyzing the correlation between the level of training and rate of accident of this particular labourer.
e. By analyzing the correlation between level of safety importance and rate of accidents for the workers in a particular company, the limits of the effective safety improvement can be predicted in order to evaluate the investment in this direction.
f. A similar technique can be applied to a particular company to predict the rate of accident in order to estimate the insurance rate for the people who work in this particular company.
g. Using the accident rate fuzzy prediction techniques companies can select the most suitable workers for any particular task

3.3. Fault location in distribution networks using fuzzy c-mean clustering techniques

In last section of this chapter we shall studies an existing 13.8 kilovolt distribution network which, serves an oil production field spread over an area of approximately sixty kilometers square, in order to locate any fault that may occur anywhere in the network using fuzzy c-mean classification techniques.

In addition, we shall introduce several methods for normalizing data and selecting the optimum number of clusters in order to classify data. Results and conclusion shall be also given to show the feasibility for the using the fuzzy logic to locate the fault location.

3.3.1. Network description

A joint venture oil company possesses two production areas, Area1 and Area2. For each area a power distribution system is provided. The power supply required for the two fields is provided from 130 MVA capacity power generation plant located in Area1. Twenty MW is transmitted to Area2 via 35KM long over head transmission line (OHTL) on wooden poles. Area2 power system also contains two 3.16 MVA stand by generators.

Area2 distribution system consists of three radial overhead transmission lines, 8-10 KM long each, serve submersible oil pumps and other loads scattered in the field (60-kilometer square). These overhead transmission lines have neither differential relays nor sectionalizing fuses. Programmable logic Controller (PLC) is connected to the incomers, outgoings and generators auxiliaries at Area2 power station. This PLC records the running and tripping information for all bus-bar compartments.

Due to the aging of the system, remote area problems and harsh desert weather, repeated faults are experienced in the grid. Because of unavailability of differential relays and/or sectionalizing fuses, it is very difficult and long time is consumed to locate any fault in this network. The problem is reflecting passively on the oil productivity of this important area.

3.3.2. Feature Matrix

In order to measure the features of the faults at 176 nodes of the network; load flow study is implemented to determine the respective power loss for each short circuit case and also short circuit study is carried out to determine the feature vector for each short circuit case.

The results, obtained from the load flow study and the short circuit study, shall be used to form the network ***feature matrix,*** which will be clustered and analyzed hereinafter. The parameters that selected to build the feature matrix are shown in Table 5.

Fuzzy clustering technique shall be used to classify the possible fault locations, which can be near to any node in the network or near to a chosen set of nodes based on the operator experience, into groups. The optimum number of groups (clusters) is computed using validity clustering technique. The remaining 13 cases are used as test cases. Euclidean distance technique is implemented to find out the group of nodes, which the fault may be found near to, for each test case.

Feeder 1	Feeder 2	Feeder 3
Set of nods fed from Feeder 1	Set of nods fed from Feeder 2	Set of nods fed from Feeder 3
Circuit breaker 1 status	Circuit breaker 2 status	Circuit breaker 3 status
Feeder 1 Short circuit Current red from substation	Feeder 2 Short circuit Current red from substation	Feeder 2 Short circuit Current red from substation
Phase Angel A1	Phase Angel A2	Phase Angel A3
Phase Angel B1	Phase Angel B2	Phase Angel B3
Phase Angel C1	Phase Angel C2	Phase Angel C3
Power dip in Feeder 1	Power dip in Feeder 2	Power dip in Feeder 3
VAR dip in Feeder 1	VAR dip in Feeder 2	VAR dip in Feeder 3

Table 5. Summary of the parameters that are selected to build the feature matrix.

Assumptions: The following assumptions are considered:

a. The temperature of the network conductors is assumed constant at seventy degree Celsius.
b. Only symmetrical short circuit is conceded. The same procedures can be implemented for any other type of faults.

Assumption (a) is valid since the transmission lines are short [47]. For assumption (b), the same work can be repeated for all other types of failures.

3.3.3. Fault location using column maximum normalization

Now, FCM technique can be implemented after normalizing the data based on column maximum values and deciding the optimum number of clusters. The results shall be analyzed in order to locate any failures may occur in the network.

3.3.3.1. Calculation procedures

To detect the fault using FCM technique with column maximum normalization the following steps have been implemented:

a. Each column in the Feature Matrix is normalized by dividing all the numbers in this column by the maximum number of the absolute values of all the numbers in the said column.
b. Cluster validity study is implemented to determine the optimum number of clusters for the normalized data.
c. FCM technique is implemented to determine the fuzzy partition matrix of the selected number of clusters.

d. The norms between each test data and the full data in the chosen cluster is examined, accordingly the corresponding cluster for each test data is decided based on the minimum norm obtained from the said examination.
e. Alpha-cut defuzzification is used with alpha equal to 90% of the average of norms between the cluster center and its data.
f. The nearest node to the fault is checked in order to determine whether it is included in the possible locations or not.

3.3.3.2. Results and discussion

Matlab program is written to implement the above six steps and the results are analyzed and summarized as follows:

a. The optimum number of cluster (twenty five) is determined by implementing cluster validity technique discussed in 2.1. The result is illustrated in Fig 35 which give the relation between the number of clusters and the corresponding error where:

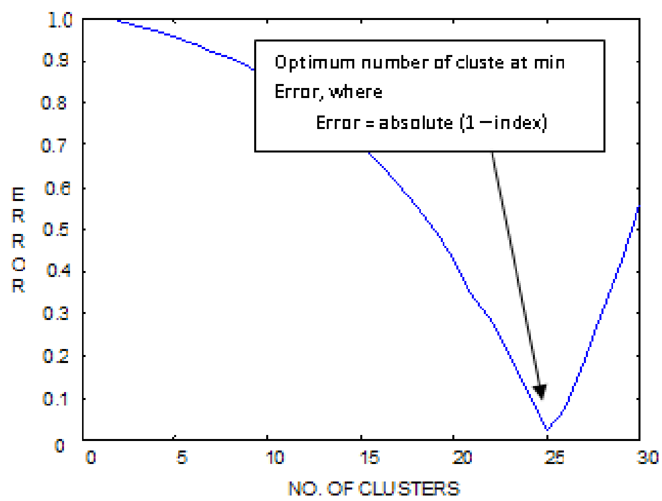

Figure 35. The relation between number of clusters and the corresponding error

b. Table 6 shows the effort saved to locate 13 fault cases. From this table, it can be noticed that:
   - Effort Saving = 1-Ratio between the number of possible locations to the total number of nodes*100%. (45)

Also, we can define the following terms:

- Percentage of successful trials (Ratio of the cases of including the nearest node in the possible locations to the total number of testing cases*100%) = 92%. (46)
- Average effort saving (Summation of the Effort Saving percentages divided by the total number of the cases) =75% (47)

It is important to notice that fuzzy cluster technique failed to locate the fault of test data number 4 due to the lack of information near to this location. However, it is expected that for more available information the performance of this technique will be improved.

TESTING CASE NO.	NUMBER OF POSSIBLE LOCATIONS	NEAREST NODE EXISTS IN THE POSSIBLE LOCATIONS	EFFORT SAVING
1	38	Yes	77%
2	38	Yes	77%
3	23	Yes	86%
4	2	No	0%
5	35	Yes	79%
6	56	Yes	66%
7	23	Yes	86%
8	49	Yes	70%
9	23	Yes	86%
10	17	Yes	90%
11	20	Yes	88%
12	20	Yes	88%
13	17	Yes	90%

Table 6. Effort Saving

3.3.4. Fault location using simple maximum normalization

Here, FCM technique is implemented after normalizing the data based on the maximum value of the data and deciding the optimum number of clusters. Then, the results are analyzed in order to locate any failures may occur in the network.

3.3.4.1. Calculation procedures

To detect the fault using FCM technique with simple maximum normalization, the following steps have been implemented:

a. All the numbers in the feature matrix are normalized by dividing all of them by the maximum number of the absolute values of all the numbers in the matrix.
b. The data are preliminary classified into clusters based on the understanding of the network operation.
c. Cluster validity study is implemented to determine the optimum number of clusters for the selected cluster.
d. FCM technique is implemented to determine the fuzzy partition matrix for the selected number of clusters.
e. The norms between each test data and the full data in the chosen cluster is examined, accordingly the corresponding cluster for each test data is decided based on the minimum norm obtained from the said examination.
f. Alpha-cut defuzzification is used with alpha equal to the average of norms between the cluster center and its data.
g. The nearest node to the fault is checked in order to determine whether it is included in the possible locations or not.

3.3.4.2. Results

Matlab program is written to implement the above six steps and the results are analyzed and summarized as follows:

a. The optimum number of cluster is determined by implementing cluster validity technique and the results are given in Table 7. It is clear from the Table that the optimum number of clusters varies from case to another, which indicates that for any considerable additional of information, cluster validity study should be implemented again to find the new optimum number of clusters.

CASE NUMBER	CASE DISCRIPTION	OPTIMUM NUMBER OF CLUSTERS
1	POWER DIP IN FEEDER #1 AND C.B.1 TRIPS	13
2	POWER DIP IN FEEDER #2 AND C.B.2 TRIPS	15
3	POWER DIP IN FEEDER #3 AND C.B.3 TRIPS	7
4	POWER DIP IN FEEDER #1 AND C.B.1 DOES NOT TRIP	10
5	POWER DIP IN FEEDER #2 AND C.B.2 DOES NOT TRIP	11
6	POWER DIP IN FEEDER #2 AND C.B.2 DOES NOT TRIP	5

Table 7. Shows the optimum number of clusters for each case identified by the operator

b. Figure 36 illustrates the relation between the number of clusters and the corresponding error in case 1, where error is calculated as given in (45).

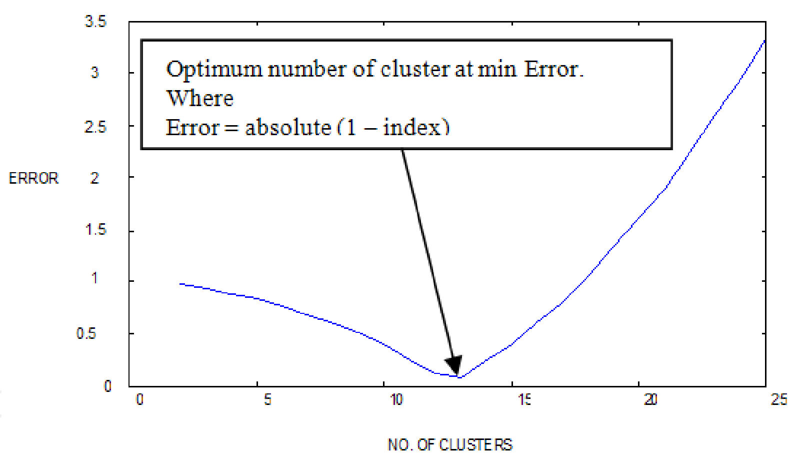

Figure 36. Shows the relation between number of clusters and the corresponding error for case 1

c. Table 8 shows the effort saved to locate 13 fault cases. From the this table , it can be noticed that:

- Effort Saving can be calculated as given in (45)
- Percentage of successful trails = 100%. See (46)
- Average effort saving = 87% See (47)

TESTING CASE NO	NUMBER OF POSSIBLE LOCATIONS	NEAREST NODE EXISTS IN THE POSSIBLE LOCATIONS	EFFORT SAVING
1	21	Yes	87%
2	16	Yes	90%
3	23	Yes	86%
4	21	Yes	87%
5	34	Yes	79%
6	14	Yes	91%
7	33	Yes	80%
8	30	Yes	82%
9	33	Yes	80%
10	5	Yes	97%
11	10	Yes	94%
12	10	Yes	94%
13	9	Yes	94%

Table 8. Effort saved

3.3.5. Discussion

The main objective of was to apply fuzzy c-mean clustering technique to locate any 3-phase fault that may occur at any point on actual power distribution network. Two different normalizing methods have been used to process the feature matrix data. The result obtained can be summarized as follows:

a. Fuzzy clustering technique can be used to investigate the location of faults in networks.
b. Any actual fault can be utilized and be fed back to the database of the clustering system to improve its performance and efficiency.
c. Understanding the network configuration and operation can be utilized to improve the clustering which gives better results.
d. Data matrix comprising the feature vectors should reflect good and adequate description of the network.
e. For any major network's upgrading or change the clustering should be implemented again by using the new data obtained from complete study of the modified network.

4. Summary of the chapter and conclusion

In this chapter we presented five new problems from different application; control, accident analysis, process and electrical network. By using fuzzy logic technique, we succeeded to resolve these problems efficiently. We also introduced different type of normalization of the data. Generating fuzzy rules by either linearization of the curves or by clustering the data were presented as well. Then a method of coloration and prediction of information using the generated fuzzy rules were provided.

Appendix

Appendix 1

Questionnaire

Form1

Case No. :

1.Personal Information

Age : 20-30 30-40 40 50 50-60

Sex : Male Female

Social Status: Bachelor Married

Height: (cm)

Weight: (kg)

Optic Status: 6/6 6/18 6/36 6/60

Hearing Ability: Very bad Bad Medium Good Very good

General Health: Very bad Bad Medium Good Very good

Adherence to safety rules: Very high High Fair Low Very low

Education: Illiterate Year 1-4 Year 4-8 Year 8-12 University

2.Work Information:

Overtime Work: Hours per week

Experience: Years

Work Nature: Mental% Manual%

Work type: Very Easy Easy Fair Tough Very Tough

Hazardous level: Very low Low Medium Hazard Very hazard

Needs of safety gear: No need Rear Sometime Always

Work location: Indoor % Office work% Outdoor%

Level of boredom: Very high High Fair Low Very low

3. Managerial Factors:

Salary received on time: Strongly disagree Disagree Agree Strongly agree

Level of training importance: Very low Low Medium High Very High

Level of safety importance: Very low Low Medium High Very High

4.External Factors:

Noise level: Very low Low Medium High Very high

Live with family: Months per year

Communication Language: Very bad Bad Medium Good Very good

5.Accident Information:

Accidents History:
(How many accidents did the case have?)

FW1	FW2	FW3	FW4	FW5	FW6	FW7	FW8	FW9	FW10	FW11	FW12
FW13	**FW14**	**FW15**	**FW16**	**FW17**	**FW18**	**FW19**	**FW20**	**FW21**	**FW22**	**FW23**	
0.4899	0.4824	0.5548	4.3318	4.3324	3.9963	4.3311	15.6376	46.6328	53.3672	3.3330	3.6684
3.6677	8.3954	19.9348	71.6699	2.6679	2.6683	3.0055	4.0012	3.3330	5.0219	3.0031	
0.3425	0.4881	0.3333	4.9983	4.3328	4.3310	4.6673	0.0000	94.9920	5.0080	3.9983	3.9999
3.3345	23.3133	6.7051	69.9817	2.9999	3.3311	3.3364	4.0020	3.0000	12.0000	3.6656	
0.1581	0.5055	0.7761	4.5545	4.6684	3.9956	4.7782	4.2714	96.6805	3.3195	3.5547	3.7724
3.1099	7.8244	45.6152	46.5605	2.8862	2.3357	3.4470	3.9988	3.6650	11.3039	4.1094	
2.8894	0.4899	0.5016	4.9953	4.9953	2.5048	3.0046	7.4857	2.5093	97.4907	3.9965	4.4954
2.9979	5.0231	14.9297	80.0472	4.4941	2.5000	2.0000	1.5024	3.0034	6.5188	3.0001	
0.3674	0.4435	0.7917	4.7499	4.4997	3.9994	4.2500	8.7491	47.4970	52.5030	3.7497	3.7497
2.7503	21.2531	28.7504	49.9965	3.2497	3.0000	2.7496	3.9992	3.7492	3.3779	3.5003	
0.6164	0.4388	0.8158	4.3160	4.3687	2.7888	3.3152	8.4245	5.0013	94.9987	3.8953	3.8950
3.2638	2.3621	0.0000	97.6379	2.9997	2.7371	2.2635	2.8957	3.4735	4.2838	3.2107	
1.2917	0.4321	0.5000	4.0000	3.7500	3.0000	3.7500	7.5000	27.5000	72.5000	4.0000	3.2500
3.0000	71.2500	10.0000	18.7500	3.2500	2.5000	2.5000	2.5000	3.7500	3.6250	3.0000	
0.3401	0.4600	0.4002	4.3754	4.3744	4.1238	4.8749	3.2411	71.2455	28.7545	3.4994	3.6244
3.2492	6.2440	61.2585	32.4975	2.4996	3.7507	3.0011	3.9998	3.1258	9.3725	4.6244	
0.8238	0.4696	0.2803	4.3322	4.3322	2.3357	4.0000	10.6568	6.7131	93.2869	3.6678	3.6678
2.6680	41.5930	11.7266	46.6804	2.6645	2.6676	2.0000	2.6649	3.6645	4.5258	3.6678	
0.5278	0.4539	0.5997	4.3992	4.2006	3.0011	4.6002	2.8065	62.0051	37.9949	3.0005	3.0005
3.2006	32.9938	43.0014	24.0048	3.4002	3.5998	2.5999	2.6004	2.4002	10.4017	3.8004	
0.2282	0.4517	0.3471	4.7537	4.8743	3.6330	4.8743	3.0413	97.4866	2.5134	3.3767	2.3770
2.3720	4.2728	83.2449	12.4822	2.8797	3.3770	4.1206	3.6233	2.4976	9.4162	4.5074	
1.1461	0.4654	0.8339	4.0001	4.2512	3.2512	3.2468	7.4926	27.4917	72.5083	3.8764	3.7486
3.3742	18.1000	13.1229	68.7771	2.8766	2.6225	3.5013	3.7523	3.5017	5.2219	3.2467	

Table 9. Illustrates the centroide matrix for the optimum number of clusters (twelve),

Feature Weight	Description	Feature Weight	Description
FW1	Accidents/ experience	FW13	Need for Safety Gear
FW2	Weight/Height	FW14	Indoor Work
FW3	Optical status	FW15	Office Work
FW4	Hearing Ability	FW16	Outdoor Work
FW5	General Health	FW17	Level of Boredom
FW6	Adherence to Safety	FW18	Salary on time
FW7	Education	FW19	Level of Training
FW8	Overtime work	FW20	Level of Safety
FW9	Mental work	FW21	Noise level
FW10	Manual work	FW22	live with family
FW11	Work type	FW23	Communication language
FW12	Hazard level		

Table 10. DESCRIPTION of feature weights,

	Personal Factors						**Work Factors**										**Managerial Factors**			**External Factors**		
	Specific weight	Optical status	Hearing ability	General health	Adherence to safety	Education	Overtime work rate	Mental work rate	Manual work rate	Work type	Hazardous level	Needs for safety-gear	Indoor work rate	Office work rate	Outdoor work rate	Level of boredom	Delay on receiving the salary on time	Level of training	Level of safety importance	Level of noise	Live with family	Communication language level
Minimum accident rate 0.1581	high	average high	average	above average	above average	high	low	high	low	fair	above average	average high	low	average	average	low	high	Very high	High	high	9-12 months per year	above average
Maximum accident rate 2.8894.	above average	low	high	good	low	low	average	low	high	tough	high	average low	low	under average	over average	high	high	low	Low	average low	4-6 months per year.	poor

Table 11. Features of the model of Maximum and Minimum accident rate

Feature	Case#1	Case#2	Case#3	Case#4	Case#5	Case#6	Case#7	Case#8
Accidents/ Year experience	2.6	3.2	2.5	2.3	3.1	0	1.1	0.125
Accident rate predicted	2.1	2.8	1.9	1.3	2.9	0.2	1.4	.17
Weight/Height	0.465	.454	.42	.466	.429	.49	.51	.415
Optical status	6/36	6/6	6/6	6/6	6/12	6/60	6/6	6/6
Hearing Ability	Medium	Good	V.Good	Good	Medium	V.Good	V.Good	V.Good
General Health	Good	Good	Good	Good	Good	V.Good	Good	V.Good
Adherence to Safety	Fair	Fair	Fair	V. High	Low	V. High	Fair	V. High
Education	16	9	12	8	5	17	10	19
Overtime work	0	8	2	1	8	0	3	0
Mental work	60	20	50	70	10	100	50	90
Manual work	40	80	50	30	90	0	50	10
Work type	Fait	Tough	Fair	Fair	Fair	V. Easy	Fair	V. Easy
Hazard level	V. High	High	Medium	V. High	High	V. Low	Medium	Low
Need for Safety Gear	Sometime	Sometime	Sometime	Always	Sometime	Rare	Rare	No need
Indoor Work	0	20	30	5	0	0	80	0
Office Work	80	30	40	45	0	100	20	100
Outdoor Work	30	50	30	50	100	0	0	0
Level of Boredom	Medium	High	Medium	Medium	High	Low	High	Medium
Salary on time	Strongly Agree	Agree	Agree	Strongly Agree	Disagree	Strongly Agree	Agree	Strongly Agree
Level of Training importance	Medium	Low	Low	Low	Low	V. High	High	High
Level of Safety Importance	High	Medium	Medium	High	Medium	High	High	V. High
Noise level	High	High	Medium	V. High	Medium	Low	Medium	Low
Live with family	12	12	6	12	0	9	12	12
Communication language	Good	V.Good	Medium	Good	Medium	V. Good	Good	V.Good

Table 12. Result of eight test cases

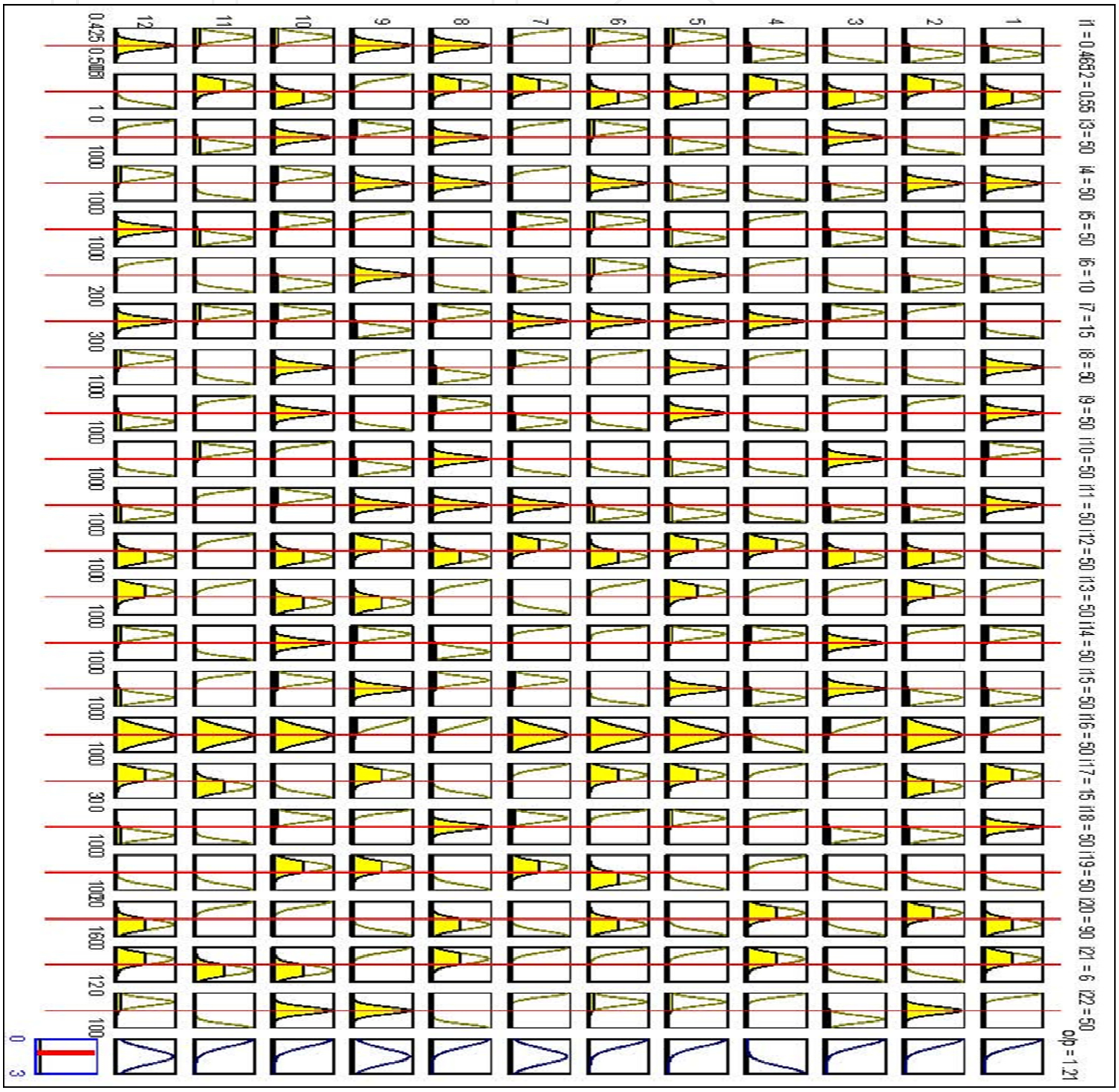

Figure 37. The output of the prediction system for `average` inputs.

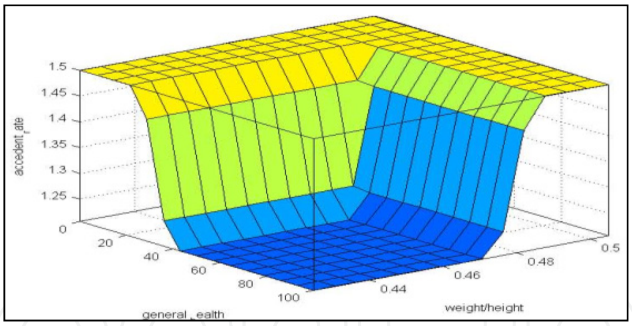

Figure 38. Correlation between weight/height, general health and rate of accident

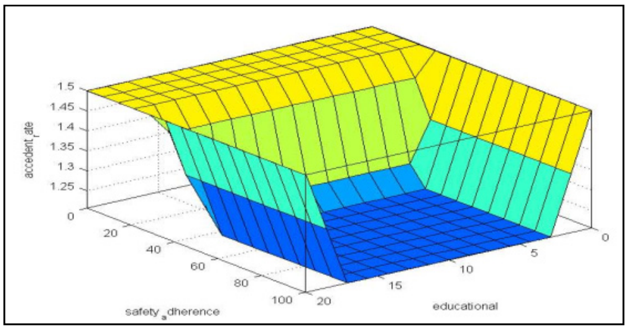

Figure 39. Correlation between education level, safety adherence and rate of accident

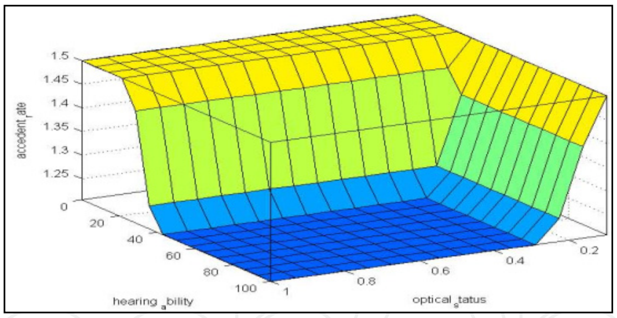

Figure 40. Correlation between optical status, hearing ability and rate of accidents.

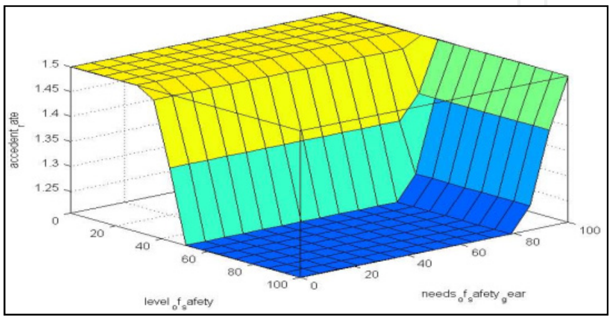

Figure 41. Correlation between level of safety, need of safety-gear and rate of accident.

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