NEURO-FUZZY BASED HYBRID METHOD FOR MODELING AND CONTROL OF PH NEUTRALIZATION

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KUALA LUMPUR

2012

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DISSERTATION SUBMITTED IN FULFILMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

MASTER OF ENGINEERING SCIENCE

FACULTY OF ENGINEERING

UNIVERSITY OF MALAYA

KUALA LUMPUR

Abstract

The pH neutralization is regarded as one of the fundamental parts of industrial chemical process. In electrochemical industry for example, heavy metals must be recovered (by reducing the solubility of the metals) from waste streams by controlling the pH value to prevent polluting the environment.

The pH neutralization shows strong nonlinear characteristics because of feed condition. Theoretically, the nonlinear effects for this process come from negative logarithm of ionic hydrogen, where process dynamic occurs when the hydrogen ions increase or decrease during neutralization process and because of dynamic nonlinearity called the ‘‘S-shape’’ curve which consists of extreme sensitivity and insensitivity regions.

This study proposes a hybrid model and a Fuzzy Logic controller for an on-line pH neutralization pilot plant. The model is used to identify the on-line pH neutralization plant’s characteristics and to improve the Fuzzy Logic controller decision output. The hybrid model is between neuro-fuzzy (ANFIS) identification technique and first principle model. The identification technique uses training dataset from experimental data to map the neutralization response curve from pH equal to 3 to 11. The first principle model is based on material balances and chemical equilibrium equation.

The objective of the proposed model is to extend the robustness effect in the Fuzzy Logic controller by predicting the control action based on on-line titrations characteristics without having to re-design the model if plant undergoes different conditions. The on-line model validation and controller performance analysis for hybrid

model and Fuzzy Logic controller was conducted and compared. The lowest values of RMSE (Root Mean Square of Error) and ISE (Integral Square of Error) are desired to justify the goodness of proposed model and controller respectively.

In the experiment, the hybrid model (in nominal plant condition, RSME = 0.1013 and in altered plant condition, RMSE = 0.5616) gives best of fit for the on-line neutralization process. The proposed Fuzzy Logic controller with inverse hybrid model is able to handle the nonlinearity and robustness issues for the on-line pH neutralization. In set point tracking analysis, it shows best performance (ISE = 35.032) compared to normal Fuzzy Logic controller (ISE = 157.652) and PID controller (ISE =195.365). Thus, the proposed hybrid model and the proposed Fuzzy Logic controller can be used effectively in on-line/off-line studies of the dynamic behaviour of the pH neutralization pilot plant.

Abstrak

Peneutralan pH dianggap sebagai salah satu daripada bahagian-bahagian asas proses kimia di industri. Dalam industri elektrokimia sebagai contoh, logam berat mesti dipisahkan (dengan mengurangkan keterlarutan logam) dari aliran sisa dengan mengawal nilai pH bagi mencegah pencemaran alam sekitar. Peneutralan pH menunjukkan ciri-ciri tak linear yang kuat adalah kerana kadar keadaan aliran masukan. Secara teori, kesan tak linear bagi proses ini datang daripada logaritma negatif ion Hidrogen, di mana dinamik proses berlaku apabila ion Hidrogen peningkatan atau penurunan semasa proses peneutralan. Proses ketaklelurusan dinamik ini dipanggil "bentuk-S" terdiri daripada rantau sensitiviti melampau dan kekurang sensitiv.

Kajian ini mencadangkan satu model hibrid dan pengawal Fuzzy Logic untuk peneutralan pH secara on-line pada loji perintis. Hybrid model ini digunakan untuk mengenal pasti ciri-ciri peneutralan pH secara on-linedan model ini dapat meningkatkan keputusan keluaran pengawal Fuzzy Logic. Model hibrid adalah kombinasi antara neuro-fuzzy (ANFIS) dan model prinsip pertama.Teknik pengenalan yang menggunakan dataset latihan daripada data eksperimen adalah bagi tujuan pememetaan keluk tindak-balas peneutralan pH daripada ph 3 hingga pH 11. Model prinsip yang pertama adalah berdasarkan persamaan keseimbangan bahan dan persamaan keseimbangan kimia.

Objektif model yang dicadangkan bertujuan untuk melanjutkan kesan kekukuhan dalam pengawal Fuzzy Logic. Hal ini dapat dijayakan dengan meramalkan tindakan kawalan yang bersesuaian berdasarkan ciri-ciri titratan dalam talian tanpa perlu mereka-bentuk semula model atau pengawal jika loji perintis berubah keadaan yang berbeza.

Pengesahan model dalam talian dan analisis prestasi pengawal bagi model hibrid dan pengawal Fuzzy Logic telah dijalankan dan dibandingkan. Nilai terendah bagi RMSE (Root Mean Square Error) dan ISE (Integral of Square Error) adalah dikehendaki untuk menunjukkan kebaikan model yang dicadangkan dan pengawal masing-masing.

Dalam eksperimen, model hibrid (pada keadaan logi nominal, RSME = 0.1013 dan dalam keadaan logi yang diubah, RMSE = 0.5616) memberikan yang terbaik yang layak untuk proses peneutralan on-line. Pengawal fuzzy logic dengan model hibrid songsang yang dicadangkan adalah mampu menangani isu-isu ketaklelurusan dan kekukuhan bagi peneutralan pH on-line. Dalam analisis pengesanan titik set, ia menunjukkan prestasi yang terbaik (ISE = 35.032) berbanding pengawal fuzzy logic yang biasa (ISE = 157.652) dan pengawal PID (ISE = 195.365). Oleh itu, model hibriddan pengawal fuzzy logic yang dicadangkan boleh digunakan secara berkesan dalam kajian kelakuan dinamik bagi logi perintis peneutralan pH secara on-line /off-line.

Acknowledgment

In the Name of Allah, the Beneficial and the Merciful.

First, I am grateful to my supervisor, Professor Ir. Dr. Mohd Azlan Hussain and co-supervisor, Associate Professor Dr. Rosli Omar for their support and interest during my postgraduate research.

Indeed, I could not have been able to complete my dissertation work without their inspiration. I would like to thank the Chemical Engineering Department, University of Malaya. I am indebted to Dr. Khairi Abdul Wahab and postgraduate classmate, Mr. Shazzad Hossain at Chemical Engineering Department.

For financial support provided during my postgraduate study, I am grateful to E-Science Fund and University Malaya Power Energy Dedicated Advanced Centre (UMPEDAC) for financial support during the candidacy.

Finally, I would like to thank my parents, wife, brother, sisters, and families for their support.

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Nomenclature

[H+]	Concentration of ion hydrogen
[OH-]	Concentration of ion hydroxyl
a_i (pH)	Ionic activity
C	Concentration, mol/litre
d(t)	Disturbance
e	Error between the plant output and set point
F	Flow rate, litre/min
f i	Function
J	Objective function
k	Step time
Kd	Derivative gain
Ki	Integral gain
Kp	Proportional gain
K_v	Control valve gain, millivolt.min/litre
Kw	Water equilibrium, 10 x 10-14
N	Total number
O	Node
pH	Potential of hydrogen
r(t)	Set point
rpm	Radian per minute
t	Time, min
td	Time delay, min
Tv	Control valve time delay, min
U	Control action, millivolt
V	Volume, litre
w_i	Weight
x_i	Input data
y(t)	Output

Greek letters:

α	Hybrid weight
μ	Input membership function
νR	Activity value
ϕ	Activation function

Subscripts:

A0	Initial concentration of acid
B0	Initial concentration of base
a	Hydrochloric acid
b	Sodium hydroxide

Abbreviations:

HCL	Hydrochloric acid
ANFIS	Adaptive Neuro Fuzzy Inference System
CSTR	Continuous stirred tank reactor
fis	Fuzzy inference system
FLC	Fuzzy logic controller
FLC	Fuzzy logic controller
ISE	Integral of error
LR	Learning rate
MF	Membership function
NaOH	Sodium hydroxide
N-N	Neural Network
PD	Proportional derivative
PI	Proportional integral
PID	Proportional integral derivative
RMSE	Root mean square of error

Chapter 1 : Introduction

1.1 Research background

The need for control in chemical plant is to ensure the production floor performs smoothly. The concern of control is to ensure that process-variables like temperature, pressure and flows are performing at nominal state. The plant behaviours are dynamic in nature, they can affect other factors such as safety, environmental, and production costs, if they are not properly controlled.

1.2 Problem statement

The pH neutralization process is widely applied in Chemical Engineering such as in coagulation-flocculation, oxidation-reduction, solvent extraction, hydrolysis and electrolysis reaction, power generation, and so on.

In pH neutralization plant, the need for a good controller is of the upmost important. The pH neutralization is hard to control and model. There are various difficulties when controlling pH in on-line chemical plants. The difficulties are high nonlinearity effect, large time delay, unknown composition of mixture, uncertainty conditions, sensitive control-action at neutralization point and many more.

The pH neutralization shows strong nonlinear characteristics because of feed components. It is because of ion interactions in mixing tank reactor. In theory, the nonlinear effects for this process come from negative logarithm of ionic hydrogen. The process dynamic occurs when the hydrogen ion increases or decreases during neutralization process.

Large time delay is another problem in controlling pH value. This effect is caused when the mixing vessel for neutralization process is too large. The reaction between acid and base would take some time before it reaches the desired state. Therefore, the time delay plays an important role for the success in model design. The proper selection of input-delay at empirical model design can overcome this problem.

The pH neutralization characteristic responses vary with the ionic strength in acid and base solution. In general, strong acid and strong base would give different characteristics compared with weak acid and weak base reaction. In practice, pH plants are easily exposed to many variations since the compositions in supply solution are not standard. For instance, in effluent water treatment, treated stream contain inconsistence ionic strength which gives difficulty to design a general model and control. As a result, the model and the controller have to be redesigned to fit with the new condition.

The described problems in modelling and control of pH neutralization above would make developing general model and control impossible. However, many researchers identified this problem and proposed advanced solutions that improved the control performance and robustness issue related to on-line pH neutralization. The findings are mainly on solving robustness issue and eliminate nonlinear barrier in designing advanced controller (Details on recent study on model and control of pH neutralization are in “Literature Review” chapter).

1.2.1 Hybrid modelling and control

The study examined several models related with pH neutralization characteristics. The designed models are not necessarily in mathematical equation or single type model. It can be in graphical block presentation, parametric equations, a combination of different model techniques or many more. The aim is to design a good model that is used to improve the advanced controller quality to solve the problem as mentioned before.

A hybrid model is a combination technique between two different methods. In general, it is like marriage affiliation that cooperates to cover-up the disadvantages between two models. Thus, we designed a hybrid model, which produced great prediction of pH value (as shown in “Research Methodology” and “Result” chapters).

The control system used in this study is from a feedback-loop that drives the error of set-point and process-variable to zero. The important part in this loop is the controller-element since other elements (final-control-element, measuring-element and process) are already considered in preliminary pilot plant design. It is the focus of the research besides model development and on-line implementation.

This study selected a Fuzzy Logic controller as the controller-element in the loop. It is selected because Fuzzy Logic has the capacity in handling nonlinear issues The challenge of this controller is that the Fuzzy Logic needed “direct” knowledge about the controlled plant. Except for this challenge, Fuzzy Logic is a universal controller, which can be expanded by using other controller mechanics very-well, for instance PID. In this study, we designed a controller based on Mamdani and Sugeno type fuzzy inference and the control performances were observed. After comparing the performances, we select Sugeno type fuzzy inference since it shows a good performance and it has the capacity to combine with the designed hybrid model above (which is described in "Research Methodology" chapter). As a result, a novel hybrid Fuzzy Logic is proposed with great extent of controller quality for on-line pH neutralization.

1.2.2 On-line pH neutralization control

The study used a pilot plant to study the pH neutralization process. It consists of a continuous stirred tank reactor (CSTR) with recycle stream, feed tank for acid and base, acid and base pipeline, and many more (which is discussed in "Research Methodology" chapter).

This study carried out on-line control based on feedback loop mentioned before. A computer managed the complete feedback loop by receiving the process-variable (in voltage signal) from Measuring Element (pH transmitter), compute the control-action based on the designed controller, and sends the control-action (in voltage signal) to Final Element (control-valve) by data acquisition hardware. This cycle is repeated continuously until the control system stops.

The on-line investigation is far different from the simulation study. It is a real test to prove the designed controller works and performs in real condition. Not many-advanced controllers succeed in real implementation. It is because of over specification or under specification of the control requirements.

In model design, an open loop experiment is carried out. The open loop control is the same as in feedback loop but the control-action is coming from human command instead of controller. The acid and base flow rate (input) and pH response (output) are observed. The dataset for on-line pH neutralization is collected from several input-output variations. This dataset is called training and checking dataset, which is used to design an empirical model by identification technique as in “Research Methodology” chapter. The designed model holds if and only if the prediction fits with on-line validation of pH at pilot plant (with or without disturbance).

1.3 The research objectives

This study is about model and controller design for on-line pH neutralization.

The objectives are:

(1) To design a hybrid pH neutralization model and validate on-line,

The purpose of designing the hybrid model and Fuzzy Logic controller is to get a robust and a good fit of model that holds the on-line characteristic of pH neutralization. As this model holds, an advanced controller as well as control-strategies could perform better compared with inaccurate and un-robust pH neutralization model.

(2) To improve a Fuzzy Logic controller by modified Fuzzy Inference System using Model Identification technique for on-line pH neutralization.

The design involves a standard Fuzzy Logic control structure and System Identification by ANFIS method.

1.4 Research scope

This study needed fundamentals on process control, Fuzzy Logic and Model Identification theory. The ideas of fuzzy set theory and Fuzzy Logic are discussed and detailed discussion on Process Control theory, pH Neutralization, Fuzzy Logic and Model Identification could be referred to establish literatures (McMillan & Cameron, 2005), (Shinskey, 1997), (Zadeh, 1994), and (Lennart, 2010).

This research focused on the following motives: (1) pH neutralization modelling, (2) analysis and controller design, (3) and on-line implementation.

Modelling is a technique to design a model that represents ideal conditions of a physical plant. It describes the physical interactions of model parameters used in the plant. In this study, the first principle of mass and energy balance from conservation law is used to get the physical model. The study also examines the other modelling technique, covering the empirical modelling techniques for pH neutralization, which is neural-fuzzy model (ANFIS). From these techniques, we designed a hybrid model for on-line pH neutralization. The selections, justification, and model development is discussed in several chapters in this dissertation. As the outcome, the hybrid model is obtained and analysed for controller design purposes.

This study conducted a qualitative and quantitative analysis for Fuzzy Logic controller. In the quantitative point of view, the analysis covered performance controller for set-point tracking and load rejection. While for the qualitative measure, offset, overshoot, and time response is typical criteria for a good quality controller. In general, good quality controllers could give process-variable response with less overshoot, fast time response, minimum offset and able to keep the performance for any variation of disturbance. As this standard follows, the designed controller should perform at the desire state and within allowable limit without any problem.

In overall outline, the dissertation is organized as follows;

Chapter 1 describes an introduction to the study background, problem statement, hybrid modelling and Fuzzy Logic controller, and on-line implementation of pH neutralization. This chapter states the objectives and highlights the novelty of the study.

Chapter 2 is dedicated to literature review, which looks at of related work by other researchers in pH neutralization modelling and control. It starts with reviewing a basic concept of process control system in pH neutralization. This is followed by recent pH neutralization study based on ideas, problems, and hybrid mechanic, which have been successfully implemented in literature. This chapter ends with analysis used by other researchers on model and controller performances.

Chapter 3 gives a detailed work method of our study. It consists of the models, hybrid model, and Fuzzy Logic controller design development. Neural fuzzy modelling (ANFIS) is described in detail. This chapter starts with models and controller design consideration. Then, it provided the design of a conventional PID (Proportional-Integral-Derivative) controller, Fuzzy Logic controller, and the proposed hybrid Fuzzy Logic controller. This chapter also describes the method for conducting analysis for model and controller performances. The specifications of instrumentation and hardware, and on-line experimental setup are provided at the end of the chapter.

Chapter 4 caters for model and controller performance results, which are obtained from simulation and on-line study. The results are mainly on controllability for set-point tracking and disturbance rejection. The robustness issues are discussed in last subsection in this chapter.

Chapter 5 discussed the observations of results taken from the previous Result chapter. The discussion focused on controllability, and observation of quality for the designed models and controller.

Chapter 6 is to conclude the study objectives, novelty and possible future work.

Chapter 2 : Literature Review

This chapter describes relevant issues to achieve research objectives in pH neutralization. It includes the process introduction, type of controller used, modelling and controller technique used and analysis method. It covers the pH neutralization model and control development from simulation to on-line basis.

2.1 Introduction to process control system

Process control terms only apply to chemical engineering automation as in petro-chemical and others continuous chemical processes (Chu *et al.*, 1998), It differs from other control engineering applications and yet shares the same theory. In general, process control is different from other engineering applications because it deals with process time delays, large time constants, uncertainty, nonlinearity, and un-model behaviour. Hopgood *et al.* (2002) has classified process control into three types:

1. Open loop control
2. Feed forward control
3. Feedback (closed loop) control

Before process control and automation, plant operator adjusts the plant parameters manually (open loop process control, see Figure 2.1a). It may be a straightforward and easy to use manual control but it becomes problematic for complex unit operations. Furthermore, its limitation is due to human error and quality of the control action.

Feed forward is a corrective action that gave control action for future response (see Figure 2.1b).

However, process control system in closed loop, promises an automatic control strategy with less human effort for the plant operator.

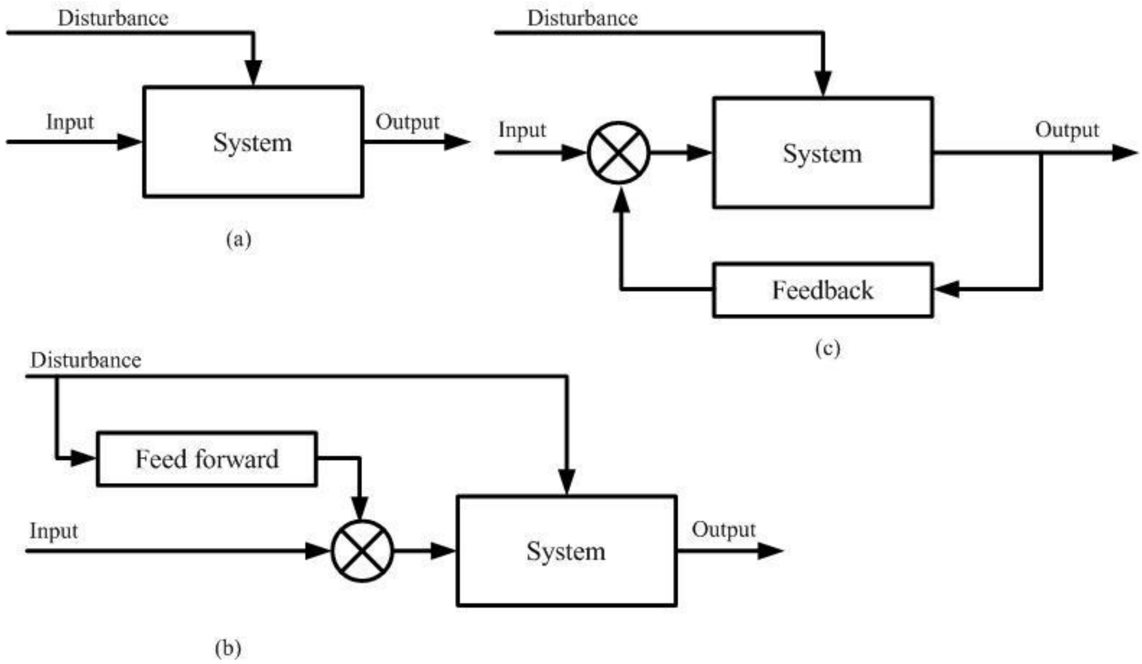


Figure 2.1: Process Control System type
(a) Open loop (b) Feed-forward (c) Feedback

Process control system as shown in Figure 2.1c is a feedback closed loop process control. It has process as unit operation to be controlled, measurements such as transmitter (process variable) in unit operation, reference, controller, and manipulative variable (final element) such as opening valve, heating element and so on. The main objective in process control is to bring the process variable to reference point by tuning manipulative variable. In many cases, control system has plant output y(t) which measure in measurement block and compared to reference block as an error e(t). Then, e(t) is fed into controller block so that controller can calculate control output, u(t), before final element block decide how much of the manipulated variable should be used. These processes will continue until the desired reference value is obtained.

In theory, process control must have four components to complete close-loop. It is a process (model or real physical plant), controller, actuator, and sensor. Figure 2.2 shows a typical block diagram for the close-loop.

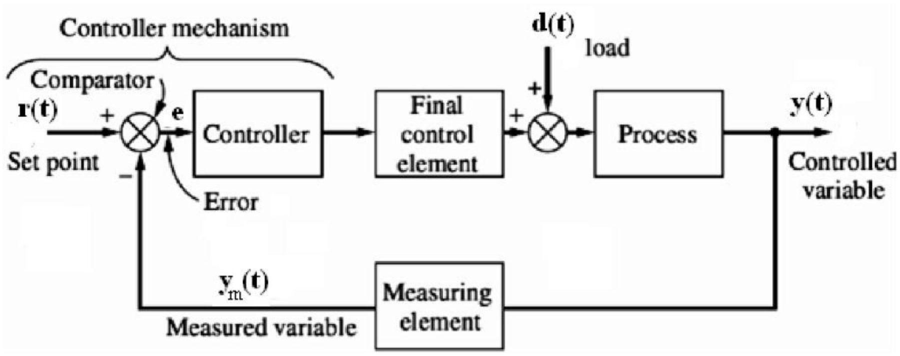


Figure 2.2: Typical process close-loop in process-control system
(Coughanowr & LeBlanc, 2008)

2.1.1 Model and physical process

Model is relatively describing the physical process dynamic behaviour. The depth of considerations in modelling could present better plant characteristic. In some cases, good model would make the engineer or researcher more comfortable in implementing real process plant. However, models are difficult to obtain and normally have limitation on present the plant characteristic due to unknown relationship, complex system or hardware limitation. In literature, there are several methods to model the process system. There are;

1. Physical relationship by considering the conservation of law
2. Empirical relationship by utilizing the heuristically data
3. Parameters approximation from physical relationship and heuristic data

Mathematical derivations of following application are based on physical relationship of first principle of mass and energy balance. The model represents the process dynamic as pre attempt to design the controller and implements to online applications. Dynamic behaviour, can be used to perform a performance analysis for selected plant beforehand for instance, stability analysis.

2.1.2 Controller and advanced controller

Controller is the brain of the process control system. It should have an adequate control action to maintain and kept the desired process value at the plant.

Controller study in process control engineering has become more attractive topic as computing technology evolved. Many techniques have been found in literature regard to process control. This field never becomes saturated topic since there is no absolute method in control problem and in addition, difference plants have different control solution. Researcher has disclosed many suggestions, improvement, and finding in classical to modern method in process control engineering.

Any control system utilizes an advanced controller in control strategy, which above a classical Proportional, Integral, and Derivative (PID) controller can be classified as advanced control system. In this study, Fuzzy Logic (FL) is selected as advanced controller since it inherit classical and modern method in it framework. Fuzzy Logic has been studied for decade in various fields of studies. In process control, Fuzzy Logic promises a good solution for modelling and control a chemical process plant. While, the Fuzzy Logic framework is a linguistic based, make it closed to human knowledge compared to others control strategy available in literature. In this study, basic Fuzzy Logic system has been carried out and a novel control strategy used Fuzzy Logic is proposed. Nevertheless, PID controller is designed for comparing control performance and effectiveness to propose control system.

2.2 Current study of pH neutralization process

In the past decades, several models for pH neutralization were developed from lab to industrial scale. A rigorous approach to model the pH neutralization has been studied in controlled stirred tank reactors, by assuming well-mixed tank, isothermal and electrically neutral solution (McAvoy, 1972) . The model is gained from mass balances and chemical equilibrium. The modelling approach offered in their work is strong acid and strong base. Later, the developed model is extended from modelling to control purposes by Wright and Kravaris (1995). Their work simplified the model derivation by taking the overall ionic activity in aqueous mixture as a linear first-order equation. While the logarithm of remain concentration of hydrogen ion (nonlinear affect) is treated after the linear equation. This approach is valid because Bronsted's acid-base idea is followed.

Gustafsson *et al.* (1995) used Bronsted's acid-base idea to obtain the pH neutralization model. Their research encompassed the chemistry of acid-base neutralization model to be used in control applications. The effects of dissociation constant, ionic strength and temperature have been considered in their developed model. Additionally, their study is useful to build nonlinear pH models regardless of acidity-alkalinity level or acid-base solution consisting of metal complexes and solid. However, in real implementation, pH neutralization plants are subjected to many unknown ionic activities and compositions, which may increase the model complexity. On the contrary, the mathematical model alone is not enough to reproduce real plant performance of certain processes and it is not accurate for online applications.

Recently, many researchers identified pH neutralization model by using advanced modelling techniques (Akesson *et al.*, 2005; Altinten, 2007; Chaudhuri, 2001; Tan *et al.*, 2005; Wang & Zhang, 2011). The advanced modelling approach is used to reduce model development, to include the un-model parameters and to study its complex behaviour. In addition, the empirical model held by this technique can give an exact characteristic of modelled process and solve the robustness issue related to on-line pH neutralization. With evolution of computing technology, achieving the best fit of empirical model is not impossible.

Many tools can be cooperated using computational algorithm to gain the best empirical model. For instance, Mwembeshi *et al.* (2001, 2004) introduced 'Global First Principles' of pH neutralization model which was embedded with feed forward Neural Networks arrangement intended for networks testing and training .The networks were trained (Levenberg-Marquardt and heuristic gradient optimization) by using past input-output in the dataset to emulate the titration characteristic. Apart from that, their Neural Network models demanded the reaction invariant species, chemical equilibrium, and electro-neutrality as identical with research by McAvoy (1972). Unfortunately, the network strategies are usually different for each types of acid-base neutralization process. Thus, the system will not be robust, as the network has to be redesigned according to the system being modelled.

On the other hand, Fuzzy Neural approaches were used to model the pH neutralization characteristic (Nie *et al.*, 1996). Three techniques in fuzzy neural model were proposed. It included the unsupervised self-organizing counter propagation algorithm, the supervised self-organizing counter propagation algorithm, and the self-growing adaptive vector quantization algorithm. The model of two-output variables employed reaction invariant ideas where the prediction represented in the study are the liquid level and pH. The approaches appear effectively compared with the others especially in modelling accuracy and it is suitable for real-time applications. However, the fuzzy neural modelling has certain limit, as it requires personal with expertise in specific computing skills, knowledge, and capable of developing and regulating the complex model.

Genetic Algorithm approaches have also been used to search for optimized configuration of Takagi-Sugenno Fuzzy model which is optimized by hybrid learning of Genetic Algorithm to produce a good model (Tan, *et al.*, 2005). The pH model designed by Genetic Algorithm optimization which correlates the titration between weak acid and strong base has numerous advantages (Wang & Zhang, 2011). This Algorithm was used to get the transposed model (Weiner's configuration) of the neutralization equation for titration process. The purpose is to find the nonlinear equation parameter, which represents the ionic base concentration. However, in the pH neutralization plant, the base flow rate is typically analogous to the acid flow rate, and may reduce the Genetic Algorithm ability to fix the estimate parameters in titration curve. Therefore, it may give interference to the developed model.

Another method to model the pH neutralization is by using Wiener arrangement (Figueroa *et al.*, 2007; Gomez *et al.*, 2004; Kalafatis *et al.*, 1995).Their models were structured by designed dynamic linear subsystem in Wiener model and combined the subsystem with static nonlinear block. The least squares method was used to find the characteristic for static nonlinear block. The empirical model is characterized by the acid and base streams as input variables and pH value (denotes in acid and base molar concentration) as the output variable.

In general, artificial intelligent methods are applicable to replicate for ill-defined, unknown and complex systems (Hussain, 1999). In modelling, this technique is a useful tool in order to study the characteristic of unknown plant with high degree of model fit with unpromising robust frameworks. However, a mathematical model is more robust than empirical model if enough correlation is used, but it is difficult to gain because of several reasons (Kuttisupakorn *et al.*, 2001).

While in the pH neutralization control, there are many literatures had been established in implementing advance controller (Goodwin *et al.*, 1982; Graebe *et al.*, 1996), (Gustafsson, 1984), (Henson & Seborg, 1994; Lu & Tsai, 2007), (Narayanan *et al.*, 1997), (Sung *et al.*, 1998), (Lee *et al.*, 2001), (Boling *et al.*, 2007), (Figueroa, *et al.*, 2007) and (Salehi *et al.*, 2009). Apparently, most of them have taken pH neutralization process as a benchmark to feature those criteria.

Yi and Chung (1995) has introduced systematically design fuzzy controller. This method is robust compares to design and proven stable since it treat controller as a universal gain that drive process-variable converge to reference value [1] . It could be extended to an advance fuzzy logic controller which adapting controller output with advance method. Like Lyapunov analysis, sliding gain technique in (Saji & Sasi Kumar, 2010), self-tuning gain method in (Meech & Jordon, 1993) and many more.

Galan *et al.* (2000) have implemented pH neutralization control in real time by using multi linear model-based control strategies. His succeed to control pH process according to several linear regions in the pH process with PI controller with scheduling parameter. It has shown that the conventional PI controller is capable to give a good performance either in set point tracking or disturbance rejections. The drawback in their method is obtaining the scheduled parameters. These parameters are according to regions and the conventional PI parameter itself. Usually experience operator easily obtains all of this parameter.

Min *et al.* (2006) have expressed their idea by proposing universal learning network (ULN) algorithm into model predictive controller (MPC) to stabilize pH control scheme with long time delay. Apart from that, Figueroa *et al*. (2007) studied on adaptive controller based on Laguerre-PWL Wiener model. In their research, Laguerre model was used to represent linear dynamic model while PWL model was implied to describe non-linear dynamic model. However, throughout their research, they just emphasized on the system's stability instead of adaptive controller robustness. Salehi *et al.* (2009) have presented a simple fuzzy adaptive controller where the control law was conducted based on dynamic equations of input-output. In their paper, they also focus on the performance of set-point tracking and load rejection in the pH neutralization system. Since they compared proposed fuzzy adaptive controller with conventional PI controller, their system appeared to be more outperformed compared with PI controller like previous research. Vale *et al.* (2010) proposed Model Reference Adaptive Controller (MRAC) consists of fixed and variable adaptive gain embedded with Hammerstein-Wiener model. Their MRAC was introduced to improve the effect of dead zone on actuator by evaluating the process performance via overshoot, settling time, and Good-chart metric. Despite, some advances, their proposed controller yet had few weaknesses since they just emphasized on the instrumentation errors instead of assessing controller's capability towards servo and regulator problems regardless of the involvement of process and instrumentation deficiencies.

As an alternative control, Wang and Zhang (2011) developed Laguerre-LSSVM Wiener model which Nonlinear Model Predictive Controller (NMPC) based on strong acid-base equivalent technique. As referred to identify Laguerre-LSSVM Wiener model, the performance of set-point tracking was monitored. Mismatch correction term was embedded in their controller to compensate with the plant-model incompatibility and unknown disturbances. In their study, they used value of mean absolute errors, mean squared errors, and sum squared errors to depict the set point tracking errors. Since the analysis of robustness properties is still be considered as an unsolved problem, therefore it application on the certain processes in order to maintain the system at a desired steady state point may not be succeeded.

2.3 Controller for pH neutralization

2.3.1 PID controller

A conventional controller is commonly found in chemical plants and had made great contributions in process control applications. This controller is based on mathematical framework with combination of 3 functions: gain error, integral error and derivative error. The beauty of this controller is that it can be implemented independently of proportional gain, P controller, gain-integral, PI controller, gain-derivative, PD controller, or gain-integral-derivative, PID controller. For example, the mathematical framework of PID controller is derived as:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{d}{dx} e(t) \tag{2.1}$$

Where K_p, K_i and K_d are PID constant parameters. In theory, K_p is proportional gain is meant for lifting process variable value, K_i is integral gain to reduce oscillation effect and K_d is derivative gain used to eliminate offset between process variable and reference parameter. This combination is one of the earliest control strategy in process control. It has been tested in many applications and still maintains a good reputation compared to other controller in literature. A PID controller is commonly used in many industries nowadays and over 90% of the controllers in chemical industries today are PID controllers (or at least some form of PID controller like a P or PI controller) .This approach is often viewed as simple, reliable, and easy to understand. A standard design method for PID controller can be found in many literatures either from mathematical formulation or from empirical technique. Establish empirical method like Ziegler-Nichole can be used to design this controller perfectly. Tuning formulation for PID parameter also can be found in Cohen-Coon theory.

However, these kinds of controllers have difficulty in handling complex process plant. This framework is only capable of handling linear process plants, while for nonlinear system, only at certain region, which has been linearized, could be implemented. Furthermore, other data except error are ignored because they do not fit into the mathematical framework in the controller and this valuable information is wasted.

Therefore, the study used advanced controller such as Fuzzy Logic system to control nonlinear and complex process. Next section described a Fuzzy Logic Controller that utilizes historical data from the plant and conventional controller it will performs better control action as in objective control plant.

2.3.2 Fuzzy Logic controller

"*As complexity rises, precise statements lose meaning and meaningful statement loses precision*" – Zadeh (1965).

Fuzzy logic controller is widely known among researchers and a lot of findings have been made in process control applications. The implementation of linguistic variables like "low" or "high" make fuzzy system favour in many applications either in household appliances or industrial practice. This controller is used in many ways in control application from simple to complex control system. For instance, Fuzzy Logic was established ages ago in a washing machine produced by LG, Electrolux and many more. This application is used to monitor conditions inside the washing machine by using sensors. By implementing this controller, a machine can adjust setting parameter to ensure the best performance is achieved. As a result, user can save money by reducing water and energy as low as possible.

Fuzzy control is established and well documented by Zadeh (1965). Fuzzy Logic system has inspired researchers and engineers until today. His work is based on formulating a human language command to a standard set of knowledge based. At initial step, this fuzzy system requires a set of input and output variables based on the requirement of the process system known as a membership function. In general, the more variables taken into the system more precise the controller will be. In contrast, more rules should be supplied to system and sometime it makes fuzzy system with an abundant of unnecessary rule. The next step is to determine the type of membership function like triangular, trapezoidal and many more (see Table 2.1 below for some examples of the membership function). For example, by using triangular form we can represent large bounded values normally 0 and 1.

This study designed two types of Fuzzy Logic controller which based on Sugeno and Mamdani inferences system.

2.3.3 Mamdani type fuzzy logic controller

Mamdani's type fuzzy inference is the first fuzzy methodology systems establish using fuzzy set theory. King and Mamdani (1977) has proposed Fuzzy Logic inference to control steam engine. It has an easy approach to utilize linguistic knowledge in designing Fuzzy Logic controller. The reasons are that no mathematical equation is required and it straightforward procedure in mapping knowledge information into a fuzzy set.

2.3.4 Sugeno type fuzzy logic controller

On the other hand, Takagi and Sugeno (1985) , and Sugeno and Kang (1986) proposed a Sugeno’s fuzzy inference. It’s an equation based and has systematic procedure in fuzzy design.

Many researchers preferred this fuzzy inference since it can cooperate with mathematical analysis, adaptive technique, and it is a computational load effectives.

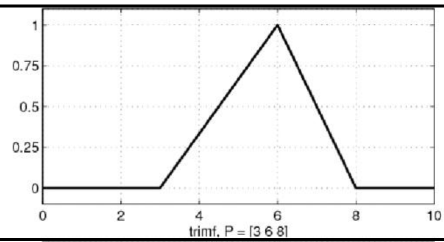
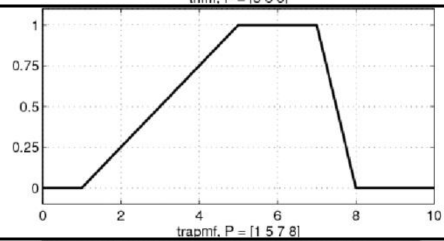
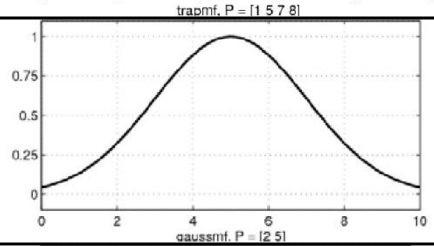
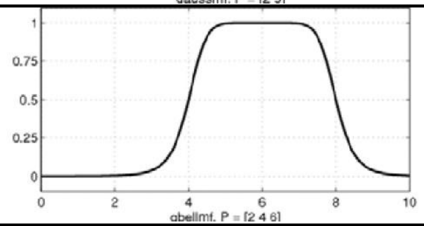
Fuzzy inferences have three similar components between both types above. They are:

1. Membership functions and linguistic variables,
2. Logical operations and
3. Fuzzy rule base, “if-then”.

Membership function (MF) is a linguistic set represented by geometric shape and is used for a conversion between crisp value and linguistic value. MF is an item inside input-output variables and it holds properties like name, range, and type. Both type either Mamdani or Sugeno, used same approaches in defining membership functions (Emami *et al.*, 2000).

In Fuzzy Logic controller, we can specify as many as membership function in input variables. However, it will be a burden on controller performance since possible unique rule is power of number membership function to input variable. Membership functions for input variables can be selected as in Table 2.1 (Tanaka & Wang, 2002) as shown below.

Table 2.1: Membership functions

Membership Functions	Graphical Illustrations
$f(x;a,b,c)=\begin{Bmatrix} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{Bmatrix}$	
$f(x;a,b,c,d)=\begin{Bmatrix} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \frac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{Bmatrix}$	
$f(x;\sigma,c)=e^{\frac{-(x-c)^2}{2\sigma^2}}$	
$f(x;a,b,c)=\frac{1}{1+\left\|\frac{x-c}{a}\right\|^{2b}}$	

Although there is a lot of membership function types in literature, Table 2.1 shows, the most commonly found in Fuzzy Logic controller membership functions.

However, Sugeno's defined fuzzy output variable in mathematical equation form is different from Mamdani's approach. In Sugeno's method, f(x,y) is a polynomial function in the input variables x and y or constant value. While, Mamdani used same approaches in defining membership function as in input variables.

Fuzzy logic is known for logical operator like AND, OR and NOT. These operators actually describe Fuzzy Logic reasoning in general. In Fuzzy Logic controller, this operator is used as a connector between input and output membership functions. The purpose of logical expression is to evaluate each membership functions value either 1 (completely true) or 0 (completely false) or range between 0 and 1. For simplicity, standard logical expression is used and is defined as in Table 2.2.

Table 2.2: Logical expression used in Fuzzy Logic controller

Method	**Operation**
AND	min
OR	max

Operator AND and OR method is used for input variables relationship reasoning. AND method is evaluated using "min" operation while OR used "max" operation. For instance, crisp value for input fuzzy variables, "error" is -0.1 in "midHigh" MF range and "rate" is 0.0 in "noChange" MF range, then this situation can be constructed as:

$$\mu_{error}\,(x_{error}) \times \mu_{Arate}\,(x_{rate}) = \mu_{error}(-0.1) \times \mu_{rate}(0.0)$$

if "error" is midHigh AND "rate" is noChange

where "midHigh" and "noChange" is one of label name for membership function in fuzzy input variables for "error" and "rate" respectively.

Membership functions and operators designed above are subjected to linguistic commands (fuzzy rules) to produce conclusions. A Fuzzy rule base consists of antecedent and consequent as human interpretation of event and action. There are many options to write fuzzy rule in Fuzzy Logic controller. For example, heuristic information from established controller like PID controller could be used. The useful information like opening a control action at saturation conditions at a certain set point, error from set point and process variable and so on. A complete Mamdani's fuzzy rule for "error" input (3 MF), "rate" (3 MF) and "valve" output (5 MF) is written as follows:

Rule 1: *If "error" is -veHigh AND "rate" is increase then "valve" is fullClose*
Rule 2: *If "error" is zero AND "rate" is increase then "valve" is halfOpen*
Rule 3: *If "error" is +veHigh AND "rate" is increase then "valve" is fullOpen*
Rule 4: *If "error" is -veHigh AND "rate" is decrease then "valve" is fullClose*
Rule 5: *If "error" is zero AND "rate" is decrease then "valve" is halfOpen*
Rule 6: *If "error" is +veHigh AND "rate" is decrease then "valve" is fullOpen*
Rule 7: *If "error" is -veHigh AND "rate" is noChange then "valve" is fullClose*
Rule 8: *If "error" is zero AND "rate" is noChange then "valve" is halfOpen*
Rule 9: *If "error" is +veHigh AND "rate" is noChange then "valve" is fullOpen*

However, Sugeno's fuzzy rule can be written as

Rule 1: *If "error" is -veHigh AND "rate" is increase then "valve" is* $f_1(x_1,x_2)$
Rule 2: *If "error" is zero AND "rate" is increase then "valve" is* $f_2(x_1,x_2)$
Rule 3: *If "error" is +veHigh AND "rate" is increase then "valve" is* $f_3(x_1,x_2)$
Rule 4: *If "error" is -veHigh AND "rate" is decrease then "valve" is* $f_4(x_1,x_2)$
Rule 5: *If "error" is zero AND "rate" is decrease then "valve" is* $f_5(x_1,x_2)$
Rule 6: *If "error" is +veHigh AND "rate" is decrease then "valve" is* $f_6(x_1,x_2)$
Rule 7: *If "error" is -veHigh AND "rate" is noChange then "valve" is* $f_7(x_1,x_2)$
Rule 8: *If "error" is zero AND "rate" is noChange then "valve" is* $f_8(x_1,x_2)$
Rule 9: *If "error" is +veHigh AND "rate" is noChange then "valve" is* $f_9(x_1,x_2)$

Where $f_i(x_1,x_2) = A_i*x_1 + B_i*x_2 + C_i$ and A, B and C are constant parameter in output functions, f_i for i = 1 to 9, while, x_1 and x_2 is crisp value for error and rate respectively (Gürocak & de Sam Lazaro, 1994). Unique possible rules that can be generated in both fuzzy rules are nine since membership functions power to number of inputs.

In process control, Fuzzy Logic system can be used either in process modelling or process control. In controller perspective, Fuzzy Logic controller is a universal controller that can be implemented in linear to nonlinear systems. In standard form, Fuzzy Logic system has four elements as shown in Figure 2.3.

They are:

i. *Fuzzification* – a process for converting crisp inputs into membership labels in fuzzy set.
ii. *Rule-Base* – stored fuzzy rule knowledge in fuzzy set
iii. *Inference mechanism* – a mapping mechanism for active membership functions between input, output, and fuzzy rule to produce several conclusions.
iv. *Defuzzification* – a compilation of active conclusions given by fuzzy inference system into a single crisp control action.

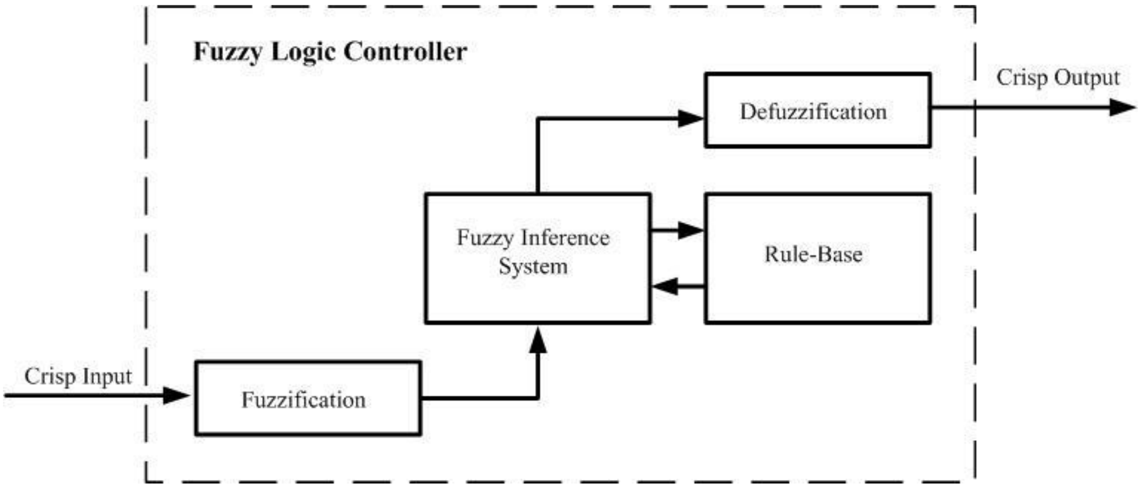


Figure 2.3: Fuzzy Logic controller

In Figure 2.3, a typical Fuzzy Logic controller used in many process control literature is presented (Filev & Yager, 1994; Maeda & Murakami, 1988; Obut & Ozgen, 2008). In this study, two inputs and one output are used in our Fuzzy Logic controller and for this reason; it will be described later in Fuzzy Logic controller design section. Actually, the number of input and output can be as much as possible depends on control system requirement. Meanwhile, the Fuzzy Logic controller operation for

Mamdani's type is as follows:

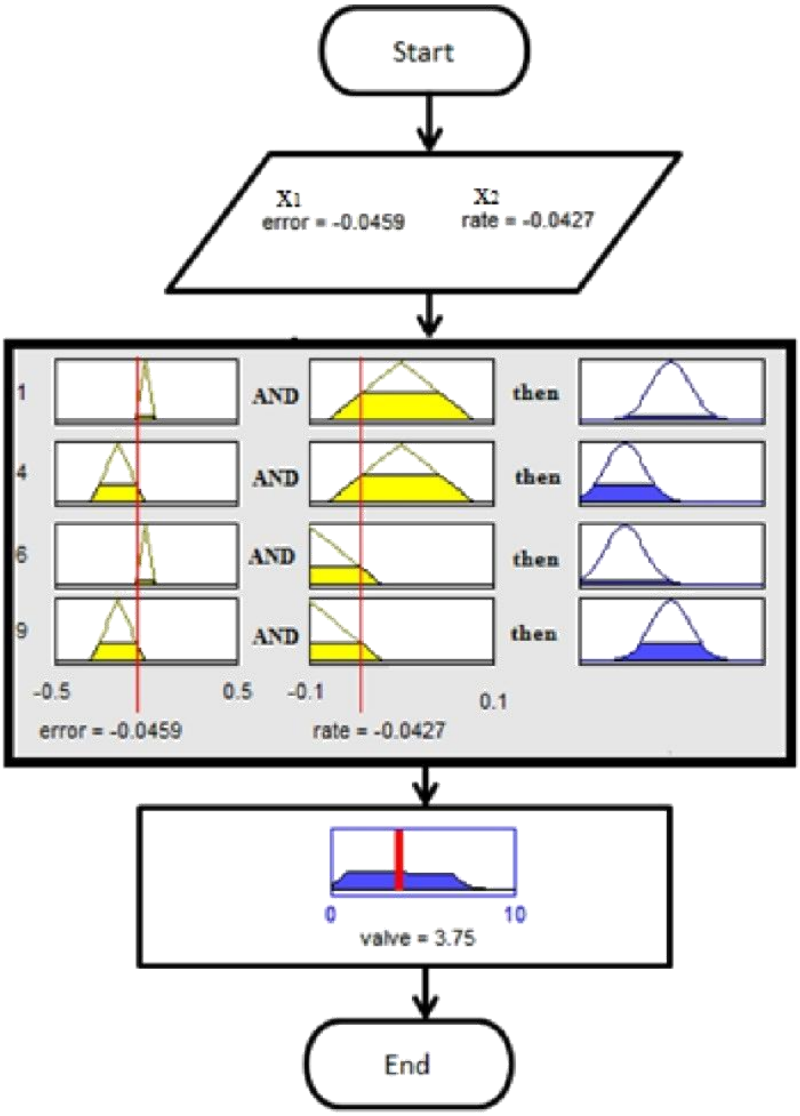
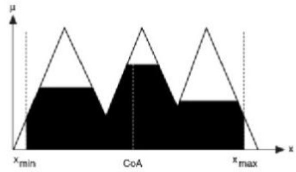
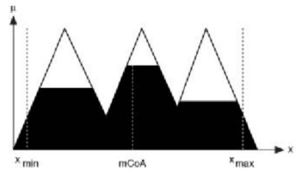
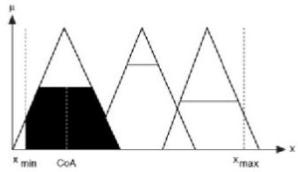
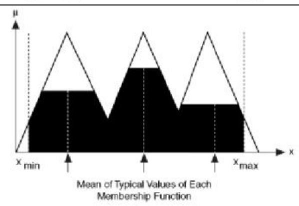


Figure 2.4: Fuzzy Logic controller operation procedure

As seen in Figure 2.4, Fuzzy Logic controller processes the crisp input into control action as output depending on fuzzy inference defined earlier. The crisp input (x_1 and x_2) could trigger any number of rules and gives several conclusions associated with the membership functions range. Then Fuzzy Logic controller concludes only single crisp value by defuzzification method. This method indicates a numeric value resulting from condition in fuzzy inference mechanism and conclusion in rule-base. Defuzzification represents action taken by controller in individual control loop cycle. Based on

Mamdani's type, there are several defuzzification methods as shown in Table 2.3 (Tanaka & Wang, 2002).

Table 2.3: Mamdani defuzzification method type

Type	**Mathematical form**	**Graphical form**
Centre of Area	$CoA = \dfrac{\int_{x_{min}}^{x_{max}} f(x) \cdot x \, dx}{\int_{x_{min}}^{x_{max}} f(x) dx}$	
Modified Centre of Area	$mCoA = \dfrac{\int f(x) \cdot x \, dx}{\int f(x) dx}$	
Centre of Sums	$x_{final} = \dfrac{CoA_1 area_1 + CoA_2 area_2 + \ldots + CoA_n area_n}{area_1 + area_2 + \ldots + area_n}$	
Centre of Maximum	$x_{final} = \dfrac{x_1 \mu_1 + x_2 \mu_2 + \ldots + x_n \mu_n}{\mu_1 + \mu_2 + \ldots + \mu_n}$	

In Sugeno's defuzzification method, control action is computed as;

$$\text{control action} = \frac{\sum_{i=1}^{N} w_i f_i}{w_i}$$

where f_i is the output function and w_i is the fuzzy rule firing strength for f_i that is being triggered (Tanaka & Wang, 2002). Fuzzy rule firing strength, w_i, can be defined as a combination of fuzzy operator (AND/OR) and input membership functions, μ_A (A is error and rate) , and can be written as

$$w_i = \text{AndMethod}(\mu_{error}(x_1), \mu_{rate}(x_2))$$

The motivation on developing the Fuzzy logic controller is because the technique can give a good performance in controlling complex chemical plant such as fermentation process, neutralization process and many more. Furthermore, it utilizes human knowledge rather than mathematical methods, which makes it more close to the system problem. For this reason, a conventional controller is less attractive than Fuzzy logic controller because it only satisfies linear process systems and simple plants.

As conclusion, Fuzzy logic control provides a formal methodology for representing, manipulating, and implementing human's heuristic knowledge. By implementing this controller into a process control system, it will minimize error in feedback closed-loop control system with less overshoot, eliminate offset and reduce oscillation effect.

2.3.5 Neural-Network

Neural network (NN) is an artificial intelligent system replicated from the human brain neuron concept. McCulloch and Pitts (1943) found neural network concept by performing mathematical processing of neuron like brain activity. Their concept represented the activity of individual neurons using simple threshold logic elements, and showed how interconnected network units could perform the logical operations. Then Rosenblatt (1962) make a generalization in neuron connection called preceptor, which is a binary classifier, which map input, x into output, f(x) in artificial neural network system.

a) Neural network structure

Neural network system consists of several nodes in input layer, hidden layers and output layer as shown in Figure 2.5 (Nrgaard *et al.*, 2000).

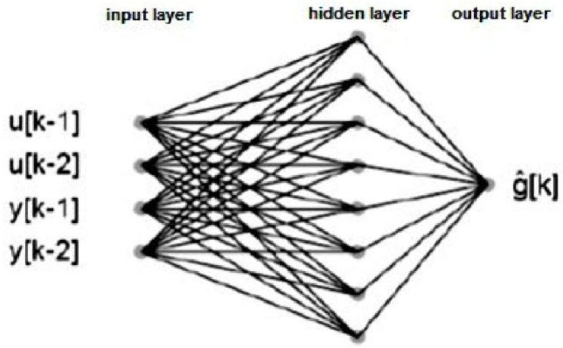


Figure 2.5: Architecture of neural network

An input node with several variations of delay is link together to form a hidden layer to generate output value based on assigned weights (see Figure 2.6) in training dataset. The determination of input delay is one of key factor to achieve a good system. While, additional hidden layer would cost computational burden to increase, increasing perceptron relation as number of node increase in power to number of layer.

b) Neural network mechanism

The operation of neural network to produces an output is as follows:

Let us consider only one node in hidden layer for the mathematical operational purposes as in Figure 2.6 (Nrgaard, *et al.*, 2000).

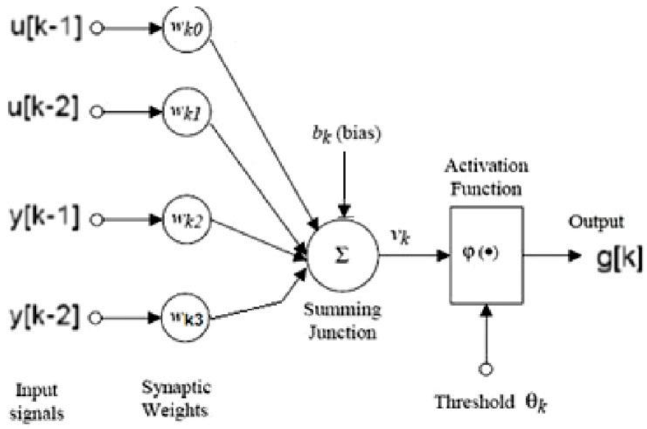


Figure 2.6: Synapse operational in single node in hidden layer

Input signals are combined into a summing junction according to establish synapse weight value w_k to produce interval activity value v_k as

$$v_k = \sum_{j=0}^{3} w_{kj} x_j$$

Finally, the output, g[k] is evaluated by some activation function, φ with value of v_k and bias, b_k as shows

$$g[k] = \varphi(v_k + b_k)$$

A threshold function θ_k could be introduced as an enhancement to the activation function. The resulting value, g[k] is an input to the output layer to produce final output, of neural network system and the mathematical operation repeat as explained ĝ[k] before.

As seen above, every neuron (node) consists of established weight like biological neuron in human brain. This weight is the so called information of action in the input system. Thus, training neural network system using input-output dataset is required to establish weight values to match process system. Additional parameters like desired output d_j and error e_j are required to be implemented inside neural network architecture as shown in Figure 2.7 (Nrgaard, *et al.*, 2000).

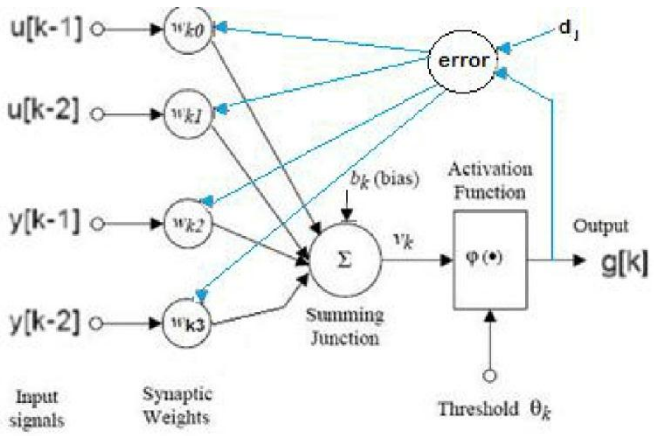


Figure 2.7: Neural network learning architecture

Learning operation is to determine w_k at every synaptic weight and it can be described as follows

$$w_{jk} = w'_{jk} + LR \cdot e_j \cdot X_i$$

Where, w'_{jk} is previous synapse weight, learning rate (LR), e_j is an error between desired and output value and X_i is input data into neural network. The mechanism of neural network learning is known as back propagation method and it is the simplest among available methods in the literature. Detailed information regarding to operational neural network and training, can be found in open neural network literature.

c) Neural network in control system

Neural network has a great influence in the process control field. Like Fuzzy Logic system, the framework does not require mathematical representation on process system as described above. The capability of neural network has excited many researchers in especially in nonlinear behaviour, time variant problem, and noisy conditions. A promising performance of accuracy is the key factor why network is most favoured among other AI systems. A lot of literature can be found regarding neural network either in process modelling or in control engineering. This technique has benefited many applications especially in Chemical Engineering field. Hussain (1999) provided an extensive review of the various applications utilizing neural network technique. In that article, neural networks are categorized under three major control schemes; inverse model based control, predictive control and adaptive control methods.

Hussain and Kershenbaum (1999) have succeeded in implementing a neural network control system for a chemical reactor both in simulation and experiment based. In their finding, neural network give outstanding performances compared to conventional control system.

2.4 Hybrid system

The hybrid system is a combination of more than one technology used to obtain a problem solution. It designed to reduce a particular technology limitation and inherit its advantages. In theory, the hybrid maybe classified into several categories as sequential, auxiliary, and embedded hybrids (Rajasekaran & Pai, 2004). These classified hybrids are described based on the interaction of technologies.

The most common interaction between the technologies is using sequential hybrid. The interaction between first and second technology is a queue-based solution as shown in Figure 2.8 below. The sub-solution from first technology is transferred to the second technology, which produces the final solution to the problem.

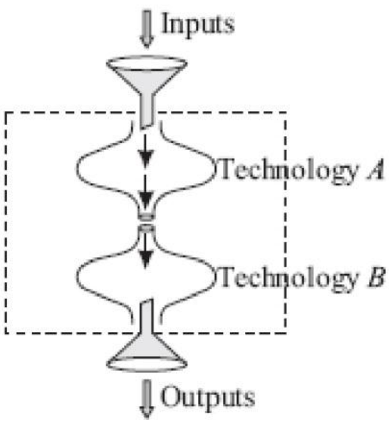


Figure 2.8: Typical sequential hybrid of two methods

Auxiliary hybrid as in Figure 2.9 is another way to combine two technologies. The interaction is divided into two parts, which is primary and secondary technology. The secondary (technology B) is providing an additional sub-solution while a primary technology is working to produce the final output. This hybrid technique is used commonly for adaptive control strategy. The controller is being supported by an approximate algorithm to produce a sub-solution that gives suggestion, while the controller produces final output for control action.

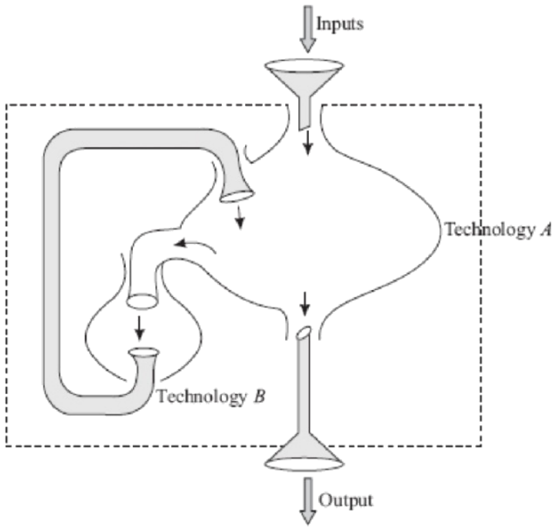


Figure 2.9: Typical auxiliary hybrid of two methods

While, embedded hybrid simultaneously produces sub-solution and the final solution is managed by technology desired most. This mechanism can be found in the most soft-computing method where in the method structure is composed of many sub-methods that gave sub-solution before the final output is compute. Neural-Network, Fuzzy Logic is one of the soft-computing tools used hardly in this hybrid. The perceptron (for Neural-Network) or the fuzzy inference (for Fuzzy Logic) is a sub-method which produces the sub-solution while the fuzzy inference compute the final output by considering the neuron weight (for Neural-Network) and fuzziness input (for Fuzzy Logic) in to the summation equation.

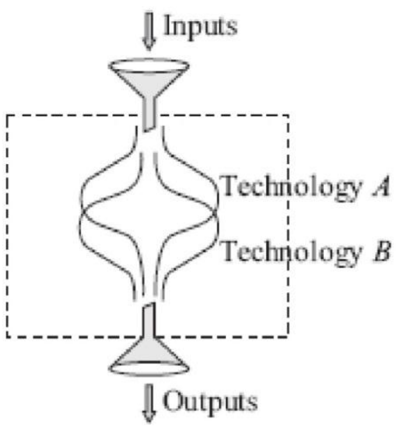


Figure 2.10: Typical embedded hybrid of two methods

2.4.1 Adaptive Neural Fuzzy Inference System (ANFIS)

ANFIS is a mixture of soft-computing tool between Neural-Network and Fuzzy Logic. The technology behind this controller is mainly from the Fuzzy Logic system and the Neural-Network tools for optimizing the configuration of the fuzzy inference system. ANFIS can be classified as auxiliary hybrid since it uses primary and secondary hybrid. ANFIS technique has been introduced by Jang (1993) by using Sugeno's fuzzy system with neural network method.

Sugeno's Fuzzy Logic system has the ability to implement mathematical equations in output function while it embraces all Fuzzy Logic system ability like mapping nonlinearity, uncertainty and variation over time in complex plant behaviour and fuzzy knowledge can be obtained from human experience. However, Fuzzy Logic controller has it drawback. For instance, it is difficult to determine the exact fuzzy rule relationship and membership functions as complexities of the plant increased. Furthermore, an extensive effort is needed in describing system behaviour since more rules are needed to tune accordingly for a good Fuzzy Logic controller.

For neural networks, to find appropriate input and output relationship (perceptron) of the process is difficult since neural network inner framework is a "black-box" in nature. In online implementation, neural network is the most expensive cost solution compared to other technologies. It requires many data in regard to the process, and data used must represent plant dynamics, and if not, this technique will have trouble in predicting output. Besides, effective neural network structure is sometime hard to construct when dealing with a complex system.

Thus, a combination of fuzzy system and neural network can improved the problems related in each technology. Although the main framework of ANFIS is Fuzzy Logic, but the configuration of Sugeno's fuzzy inference is prepared by neural network technique. The neural network technique can be used as a learning mechanism in input and output dataset. The learning knowledge could be utilized to generate a Fuzzy Logic rules and membership functions, which conventional Fuzzy Logic may took extra work. Indirectly, development activity of Fuzzy Logic controller for complex is reduced significantly.

2.4.2 ANFIS architecture

In general ANFIS architecture has the same components as Sugeno' type Fuzzy Logic system with polynomial output function $f_i(x,y)$ of input variables, x, y where i is the number of fuzzy rules used as shown in Figure 2.11 (André Jones *et al.*, 1986).

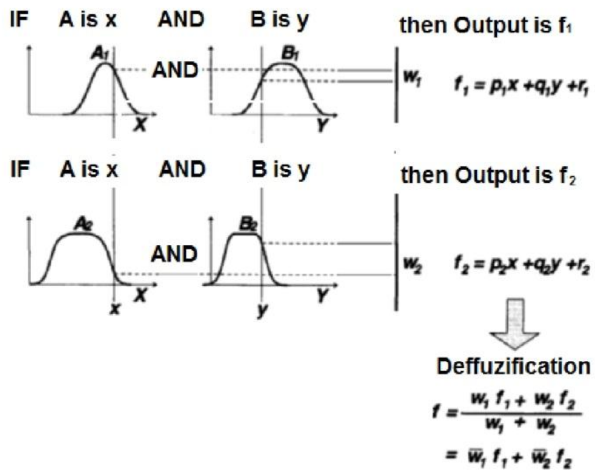


Figure 2.11: Sugeno's type Fuzzy Logic system with polynomial output function

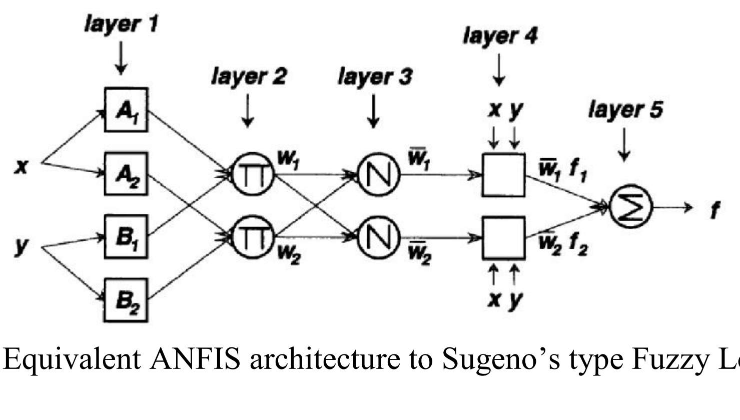


Figure 2.12: Equivalent ANFIS architecture to Sugeno's type Fuzzy Logic system

The ANFIS architecture follows the feed forward neural network and is trained using a supervised learning mechanism. The learning objective is to find the consequent equation parameters that fit input-output dataset. As shown in Figure 2.16, *fis* structure has 5 working layers as briefly described below:

1. Input layer
2. "Inputmf" layer
3. Rule layer
4. "Outputmf" layer
5. Output layer

Layer 1: Input layer – is used to convert crisp value of x and y to label as used in input membership function. The output of this node, O_1 is

$O_{1,I} = \mu_{Ai}(x)$ for i = 1,2 and $O_{1,j} = \mu_{Bj-2}$ (y) for j =3,4

As described in Chapter 3, input membership function can be selected from several types (Refer to Table 4.2).

Layer 2: "Inputmf" layer – is used to calculate the weight, w_i of relationship membership functions. The output of this node is relationship weight between input x and y.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2$$

Layer 3: Rule layer – is used to combine consequent action with input relationship. As from previous layer, this layer works to combine several active rules in fuzzy inference system and gives output, O_3, as total average weight.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}$$

Layer 4: “Outputmf” layer – is used as an adaptive platform to adjust consequent output parameter in ANFIS framework. The output, O_4, from this node performs consequent action in each active fuzzy rule.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

Layer 5: is used to compute overall output function to final output in ANFIS system

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

As described above, layer in ANFIS has similar working structure as neural network in designing fuzzy inference system. The adaptive mechanism works to adjust consequent constant parameter within several iterations by reducing error between overall ANFIS output and supplied output data set. Thus, any fitting mechanism can be used to find consequence parameters, for instance, gradient descent, least squares method, genetic algorithm, particle swarm or hybrid between those techniques.

2.4.3 Inverse ANFIS model

An accurate technique in connecting the input and output for a process plant is a major attraction in the ANFIS research. ANFIS is an attractive solution where it allows human knowledge to be used automatically to determine the control action, *u* for conventional Fuzzy Logic controllers. ANFIS provides satisfactory results in dynamic mapping process plant and this technology can be used in the control plants at any desired set point. In this study, the ANFIS model is designed to give appropriate control action for fuzzy logic controller based on the inverse model response where the input and output relations at online dataset is reversed.

Initially, input and output dataset are prepared in open loop plant. In process plant model identification using ANFIS, input data is a manipulating variable, u and the output is process variable, y. ANFIS model then is validated in real time to guarantee the trained model could predict the process variable, y for any given inputs, u. In order to design an inverse model controller, the dataset is inversed by changing the input output orientation, for instance, input dataset for ANFIS controller is taken from output dataset of model, and output dataset for ANFIS controller is from input model dataset. By doing this inversed dataset, the controller would predict control action, u for any desired process variable in process control system.

Chapter 3 : Modelling of pH Neutralization process

3.1 Model and controller designs considerations

It is important to specifying control objectives and design considerations beforehand because it would give a systematic optimized design approach.

The interested parameters are like rise-time, overshoot, and tracking specifications. In this study, the controller objectives are to achieve less overshoot, fastest rise time, less oscillation, and reduced robustness affects. To achieve the objectives, several technical ideas are considered.

First, designed controller must be able to operate for nonlinear process behaviour. This is very crucial consideration for selected a nonlinear controller. In “Literature review” chapter, we listed several recent controllers that were used in pH neutralization control-system. Fuzzy Logic controller is selected since it has the capacity to deal with nonlinear process behaviour. Detailed description will be given in the next section of this chapter. The concerned of nonlinearity for pH neutralization is at the set point of interchange regions. This is because the need of the control action is different. In neutralization region, a very small control action is required while requiring a large control action at acid and base regions. This need will give a problem to linear controllers like PID controller but not for Fuzzy Logic controller.

Second, the designed controller must be able to reduce the un-design factor due to aged plants or altered parameters. This consideration is an optional for many controlled plant engineers since the controller could be redesigned according to new working parameters. However, it will be non-economic for the production floor to shut-down and redesign the controller. Therefore, the designed controller must be able to increase robustness due to un-design factors as mentions above.

The success of a robust controller is related to the plant dynamic accuracy. Next, model accuracy is another aspect to achieve in the controller objectives. The designed model must be able to give accurate prediction of on-line pH value during control system implementation (at nominal or different working conditions). The robust controller depends on the accuracy of this model. It is importance to improve the robustness in Fuzzy Logic controller. Hence, hybrid model is introduced to give accurate model for on-line prediction.

Other considerations will be discussed in the following sections.

3.2 pH neutralization model designs

This study developed a hybrid model from first principle mathematical model and Fuzzy Logic model with Neural Network mechanism. The study propose a hybrid mechanic, which managing the models contribution to achieve best agreement in dataset. The study designed a pH neutralization model based on Figure 3.1. In the mixing tank, strong acid (HCl) flow rate and strong base ($NaOH$) flow rate are mixed which produced a dynamic behaviour in pH characteristic. The study is to predict the pH value for this problem by using hybrid modelling.

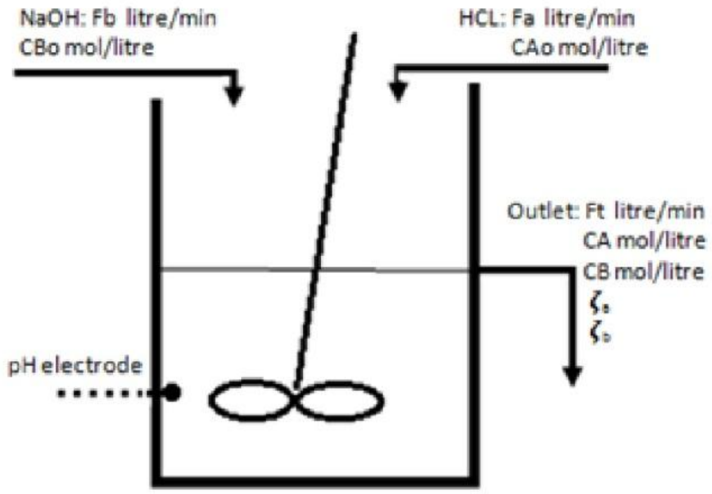


Figure 3.1: Basic design of studied pilot plant

3.2.1 Mathematical model

The mathematical model for pH neutralization process is based on material balances and chemical equilibrium equation. The model follows McAvoy (1972) and Wright *et al.* (1991) works. The mathematical model based is obtained from strong acid (Hydrochloric) and strong base (Sodium Hydroxide) reaction according to Figure 3.1. Assumptions for the model are instantaneous reaction, well-mixed, constant-density mixture, and no formation of solids during experiment. Unsteady-state kinetic model for pH neutralization is written as in Eq.3.1 below. Where V_r is tank volume, F_a is acid flow rate, F_b is base flow rate, C_{A0} and C_{B0} is a concentration for acid and base respectively.

$$\frac{dx}{dt} = \frac{C_{A^0}}{v_r}F_a - \frac{C_{B^0}}{v_r}F_b - (F_a + F_b)x \tag{3.1}$$

$$x = -\sum_{i=1}^{n} a_i\,(pH)\cdot x_i \tag{3.2}$$

Gustafsson and Waller (1983) define Eq.3.2 as the overall-total-ionic-concentration in mixed tank. The $a_i(pH)$ is identified for strong acid as -1, and strong base as +1 (Wright *et al.*, 1991). Thus, x is the remained ionic concentration in the mixture when acid and base is neutralized where x_i is an ionic concentration of reactants.

In aqueous solution, mixture of ion hydrogen and Hydroxide is electrically neutral. Therefore, electro-neutrality and water-equilibrium theories is used to express electrolyte disassociations (Eq. 3.3) by considering the system is in aqueous solution, isothermal reaction at temperature 27 ^{o}C, and water equilibrium constant, K_W at 1×10^{-14}

$$x = [\mathrm{H}^+] - \frac{K_w}{[\mathrm{H}^+]} \tag{3.3}$$

Then, kinetic model from Eq. 3.1 can be updated based on hydrogen concentration as in Eq.3.4.

$$\frac{d}{dt}\left([\mathrm{H}^+] - \frac{K_w}{[\mathrm{H}^+]}\right) = \left(\frac{C_A{}^o}{v_r} - [\mathrm{H}^+] + \frac{K_w}{[\mathrm{H}^+]}\right)F_a + \left(-\frac{C_B{}^o}{v_r} - [\mathrm{H}^+] + \frac{K_w}{[\mathrm{H}^+]}\right)F_b \tag{3.4}$$

Eq. 3.4 is a nonhomogeneous and nonlinear differential equation. A numerical tool like Eular or Runge-Kutta method can be used to solve this equation. The complete pH neutralization model is gained after solving Eq.3.4 and used that solved value at time, t into Eq.3.5 in which pH value is calculated by taking the logarithm of hydrogen concentration, as below:

$$pH_m(t;F_a,F_b) = -\log_{10}([H^+]) \tag{3.5}$$

The inputs force that is affecting the pH characteristic is mainly because of the inlet flow rate. Therefore, in this model, acid (F_a) and base (F_b) flow rates are inputs-signal, and pH value is the output-signal for the model while the rest are constants. The nominal operating parameters are referred to in Table 3.1 (Ishak *et al.,* 2001).

Table 3.1: Nominal operating conditions of pH neutralization

Parameter	**Symbol**	**Value**	**Unit**
Acid flow rate	F_a	3.5 ± 0.1	litre/min
Base flow rate	F_b	(5 to 13) ±0.1	litre/min
Initial condition of HCl	C_{Ao}	0.003	mol/litre
Initial condition of NaOH	C_{Bo}	0.003	mol/litre
Volume of mixing tank	V_r	100	litre

3.2.2 ANFIS model

Fuzzy Logic is an attractive technique for pH neutralization modelling. The study used Fuzzy Logic to gain empirical model of pH neutralization. It provided a multi-model frame for nonlinear behaviour modelling. The model is gained by assigns three crisp-inputs and one crisp-output with respect to the Eq. 3.6. The Fuzzy Logic has four parts: fuzzification, fuzzy inference, rule-base, and defuzzification (Zadeh, 1996).

In model identification, the input-crisp value can be in many forms, like flow rate, concentrations, speed of agitator, volume, and more. The possible input-output candidates for the empirical model are flow rate and pH value (see Figure 3.1). In this study, three inputs (from acid-base flow rates) and one output (from pH value) is used respectively. These inputs-output have crisp values. The input-crisp values are converted input into fuzzy-input values. The fuzzy-inputs are designed by using two generalized bell-shaped curve membership-functions, which are represented, by Eq.3.6, Eq.3.7, and Eq.3.8 while the output is referred to Eq.3.9. The inputs range is between minimum and maximum inputs in the dataset as referred to Figure 3.2 below.

$$f_1(F_A) = (1 + \left|\frac{F_A - c}{a}\right|^{2b})^{-1} = \begin{cases} f_{1,min}(F_A): & a = 1.981; b = 2; c = 0 \\ f_{1,max}(F_A); & a = 1.981; b = 2; c = 3.963 \end{cases} \tag{3.6}$$

$$f_2(F_B) = (1 + \left|\frac{F_B - c}{a}\right|^{2b})^{-1} = \begin{cases} f_{2,min}(F_B): & a = 1.981; b = 2; c = 0 \\ f_{2,max}(F_B); & a = 6.967; b = 2; c = 13.930 \end{cases} \tag{3.7}$$

$$f_3(F_B) = (1 + \left|\frac{F_B - c}{a}\right|^{2b})^{-1} = \begin{cases} f_{3,min}(F_B): & a = 1.981; b = 2; c = 0 \\ f_{3,max}(F_B); & a = 6.967; b = 2; c = 13.930 \end{cases} \tag{3.8}$$

Figure 3.2 below shows the plotted input-output dataset from on-line open loop investigation. The experiment was conducted by using nominal operating conditions as in Table 3.1. The data are collected by using NI-6221 multichannel data-acquisition hardware at sampling time of 1-second.

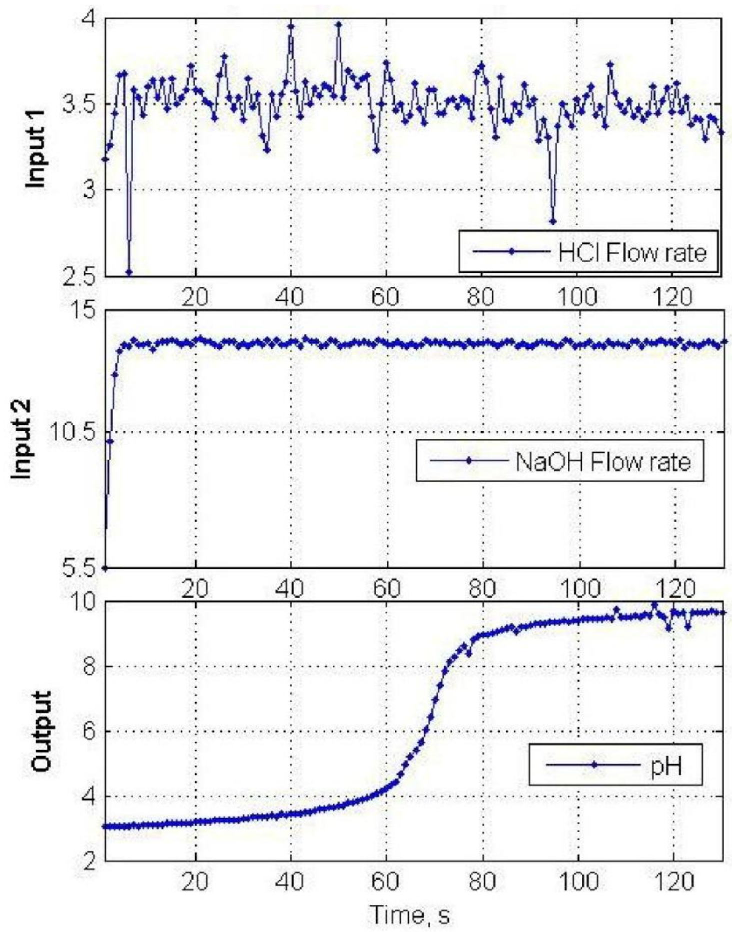


Figure 3.2: Input-output dataset for online pH neutralization

The inputs are the flow rate at different time-delay (τ_d) from the dataset (on-line measured data). The time-delay selection for flow rate can be chosen at any delayed time in dataset. For example, the acid and base flow rates can be selected at any time-delay which is from -1 to -N (N is the total row in dataset). Therefore, the output membership function is written as in Eq. 3.9 below. The optimized time-delay selection is the key to gain best fit of model besides adjusting constant coefficient (A, B, C, and D) in Eq. 3.9.

$$pH_p(k) = A\,F_a(k-\tau_1) + B\,F_b(k-\tau_2) + C\,F_b(k-\tau_3) + D \quad (3.9)$$

In inputs selection, constant coefficients (A, B, C and D) are initialized as one, while time-delay is obtained from viewing open loop response (Fig.3.2). According to Figure 3.2, the effective time-delay is between -1 to -80 seconds. Root Mean Square Error

(RMSE) is used as objective function (Eq.3.10 below) to compare the predicted pH value for ten different time-delay candidates for three inputs.

$$J = RMSE = \sqrt{\frac{\sum_{k=1}^{N}\left(\mathrm{pH_r}(k) - \mathrm{pH_p}(k)\right)}{N}} \tag{3.10}$$

Where $pH_r(k)$ is on-line pH value in dataset from k = 1,2,3 to N, which N is total number in dataset. The chosen time-delay for τ_1 and τ_2 (as in Eq. 3.9) is at -72th and -73th seconds respectively for F_b, and for τ_3 is at -40th seconds for F_a. These three inputs combination gives the lowest value (RMSE = 0.2459) according to Figure 3.3, which gives the best fit of real data in dataset.

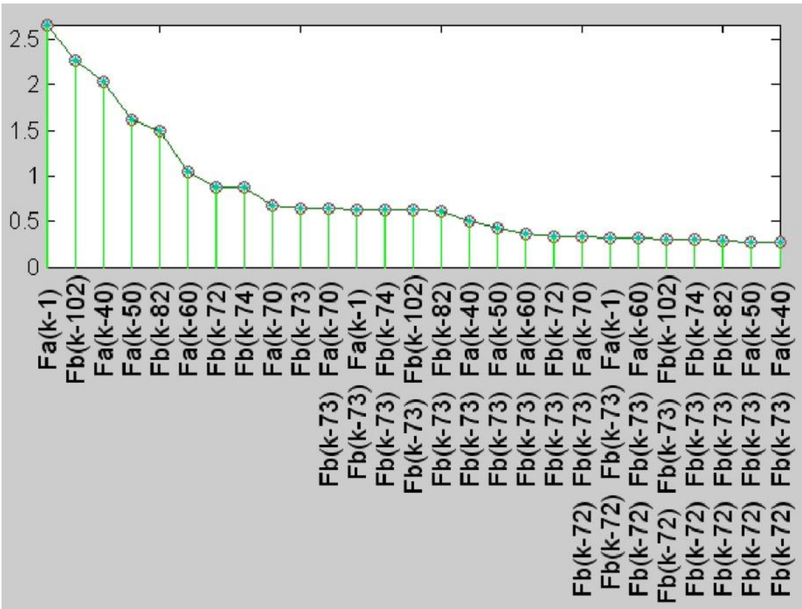


Figure 3.3: Sequential input selection for three inputs from 10 candidates

The rule-base for the model is composed by taking maximum relationship among three inputs. The rule-base is eight unique logical combinations that are from 3 inputs and two membership functions (2^3). The rules are listed as in Table 3.2.

Table 3.2: Eight unique combinations among inputs and output for fuzzy rule-base

	AND Input2 is $f_{2,min}(F_B\text{-}72)$ AND Input3 is $f_{3,min}(F_B\text{-}73)$	AND Input2 is $f_{2,max}$ $(F_B\text{-}72)$ AND Input3 is $f_{3,min}(F_B\text{-}73)$
If Input1 is $f_{1,min}(F_A\text{-}40)$	**Rule#1** : then output is $pH_1(k)$	**Rule#2** : then output is $pH_2(k)$
If Input1is $f_{1,max}(F_A\text{-}40)$	**Rule#3** : then output is $pH_3(k)$	**Rule#4** : then output is $pH_4(k)$
	AND Input2 is $f_{2,min}$ $(F_B\text{-}72)$ AND Input3 is $f_{3,max}(F_B\text{-}73)$	AND Input2 is $f_{2,max}$ $(F_B\text{-}72)$ AND Input3 is $f_{3,max}(F_B\text{-}73)$
If Input1is $f_{1,min}(F_A\text{-}40)$	**Rule#5** : then output is $pH_5(k)$	**Rule#6** : then output is $pH_6(k)$
If Input1is $f_{1,max}(F_A\text{-}40)$	**Rule#7** : then output is $pH_7(k)$	**Rule#8** : then output is $pH_8(k)$

The fuzzy-output is linear functions consisting of fuzzy-input membership function. Eq.13 can be elaborated to eight different cases as Eq.3.11

$$pH_{p,i}(k) = A_i\ F_a(k-\tau_1) + B_i\ F_b(k-\tau_2) + C_i\ F_b(k-\tau_3) + D_i \tag{3.11}$$

where i = 1,2 to 8

The coefficient function (A_i, B_i, C_i and D_i) are the gains that are needed to be optimized for best fit of pH neutralization dataset. The complete construction of fuzzy model can be seen at Figure 3.4, which have three parts (input, rule, and output) as describes in Fuzzy Logic.

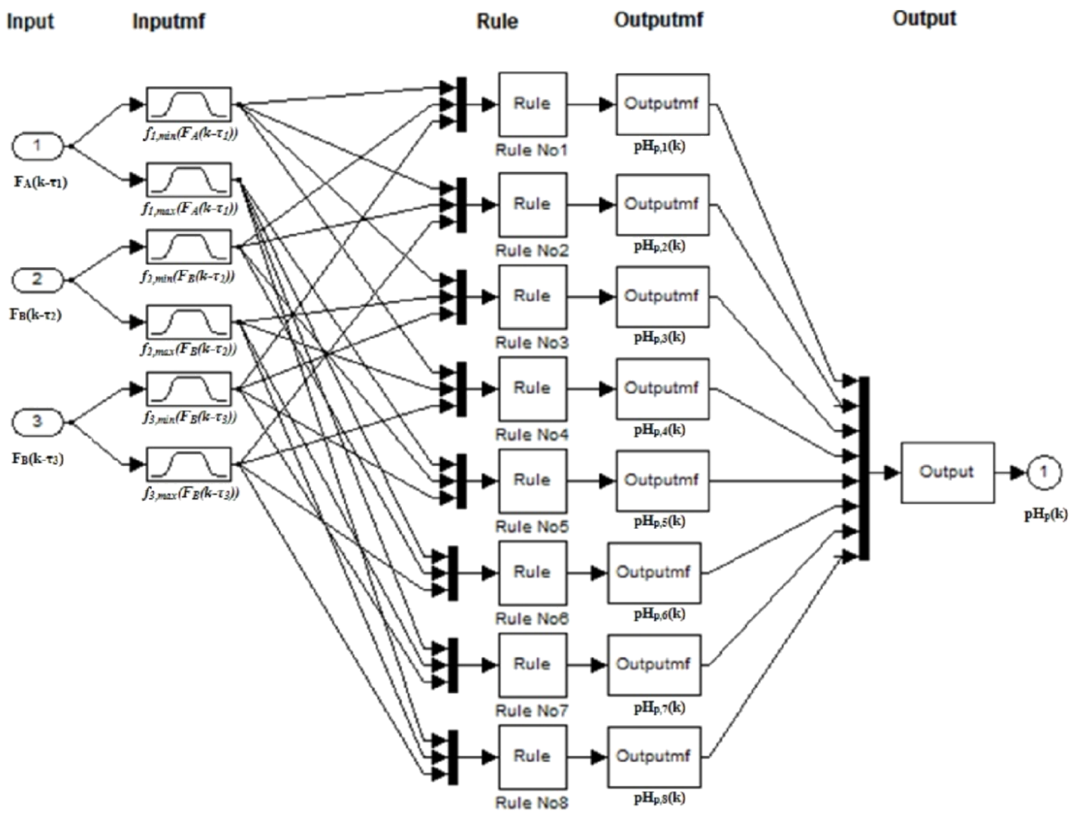


Figure 3.4: ANFIS model structure

Figure 3.4 shows likeness to ideas in Neural-Network (N-N) architecture (see Section 2.3.4). In N-N, input-signals are combined at summing junction and the node output (internal-activity value) is calculated by multiplying the synapse weight value for each signal respectively. In neuro-fuzzy case, synapse weight is the coefficient (A_i, B_i, C_i, and D_i) while the summing junction is at Eq.15 which combines the active rule-base with the synapse weight at each fuzzy-inputs to produce a crisp output-value ($pH_p(k)$).

As in Neural-Network identification, neuro-fuzzy have to train the synapse weight with the on-line dataset (Figure 3.2). Least-square method (learning algorithm) is used to get the optimized synapse weight (Ai, Bi, Ci, and Di) by iteratively reducing the cost of objective function (Eq.14) for entire fuzzy-structure (Table 3.3Table 3.3)

Table 3.3: Optimized coefficients of ANFIS output-function

i	A_i	B_i	C_i	D_i
1	0.3524	0.5574	0.03086	0.167
2	1.073	0.06756	-0.006016	-0.1915
3	-0.05421	1.057	-0.5296	0.9288
4	1.337	0.4237	0.3674	-9.853
5	0.8138	-0.4955	0.4823	4.041
6	1.255	0.1555	-0.2992	0.7469
7	0.7408	0.2627	0.0578	0.1502
8	0.1921	0.7397	0.05951	-0.2554

The final layer (control output) gives a value by summing all conclusion values. It is described as

$$Output = pH_p(k) = \sum_i \overline{W}_i pH_{p,i}(k) \quad ; i = 1,2,\ldots k \tag{3.12}$$

3.2.3 Hybrid ANFIS and mathematical model

A hybrid is also known as a combination of several techniques. This study used two different techniques, which is a combination of mathematical model and empirical model. Lennart (2010) classified the hybrid model as in "*slated grey*" colour analogy, with a combination of first principle model (*"pure white"*) and soft computing model (*"black"*).

Let us consider the dynamic continuous time mathematical model and empirical model as in Eq.3.5 and Eq.3.12 respectively as below.

$$\frac{dx}{dt} = Ax + Bu$$

$$y_{m,1}(t) = Cx \tag{3.13}$$

$$y_{m,2}(t) = D_1x(t - t_{d1}) + D_2x(t - t_{d2}) + \cdots + D_nx(t - t_{dn}) + E_1u(t - t_{e1}) + \tag{3.14}$$

$$E_2u(t - t_{e2}) + \cdots + E_nu(t - t_{en})$$

The mathematical model (Eq.3.13) is a typical physical first order continuous time domain model which presenting Eq.3.5. Next, Eq.3.14 is an empirical model constructed by historical dataset based on a modelled plant that present 3.12. Both models have different mechanics in predicting the response of the plant. Mostly, Eq.3.13 represents a theoretical formulation and Eq.3.14 is on identification from best fit of dataset. This study proposes a hybrid mechanic that can combine both methods and give better dataset agreement compared to standalone model. This study proposes a two hybrid mechanics which suitable for combining the mathematical and empirical model.

First is a parallel hybrid that is managed by hybrid weight, α as in Eq.3. The summation of output weight is always equal to one if and only if α is in range of zero to one.

$$y_{h1}(t) = \sum\left[y_{m,1}(x,u)(\alpha) + y_{m,2}(x(t - t_d),u(t - t_e))(1 - \alpha)\right] \tag{3.15}$$

The $y_{h1}(t)$ is output for hybrid model from combination of Eq.3.13 and Eq.3.14. The structure is simple and fast. The hybrid weight (α) can be a constant or function, which the value, leading the prediction toward the theoretical idea or training model. Thus, it has a capacity of predicting the process-output value within its robustness limitation.

Second, the proposed hybrid structure is constructed by using model performance weight of individual model. The hybrid model output is calculated as in Eq.3.16 where the individual output is evaluated according to their performance weight, ω.

$$y_{h2}(k) = \frac{\sum_{i=1}^{N}[\omega_i * f(x,u)_i]}{\sum_{i=1}^{N}\omega_i} \tag{3.16}$$

The structure above is for combining several models. Every i^{th} model has been assigned to a performance weight (ω_i) that can be a constant or a function. Eq.3.16 is more flexible in managing the output contribution because the summation of weight can be greater that one.

The proposed hybrid structures above can be treated as a static or dynamic equation depending on its weight. Static equation is from a constant weight while, the dynamic equation is depended on the functions used. The function can be implemented from on dynamic equation. Furthermore, proposed hybrid structure can used as on-line adapting gain for adaptive controller studies. However, the adapting mechanism requires additional algorithms to perform a dynamic adjustment in on-line basis.

The individual models have several advantages and disadvantages. The ANFIS model is used to predict the pH value based on the real plant characteristics, while the mathematical pH model is used to calculate the theoretical pH values. ANFIS duplicate the dynamics of a pH plant, which depends on training dataset (Figure 3.2). The motive of introducing the mathematical and ANFIS model is to give better pH value prediction. Subsequently, the hybrid model would extent the robust properties from nominal working condition. The variations are acid and base concentrations, reactor volume, mixing agitator speed, unknown compositions, and many more during on-line implementation.

The hybrid models (Eq.3.17 and Eq.3.18) for pH neutralization are designed by combining Eq.3.5 and Eq.3.12. Both models are considered in discreet time domain which sampling time (h) is one second as in dataset (Figure 3.2).

$$pH_{h1}(k) = \sum\left[pH_m(k;F_{HCl},F_{NaoH})(\alpha) + pH_p(k)(1-\alpha)\right] \tag{3.17}$$

or

$$pH_{h2}(k) = \frac{(\omega_m) pH_m(k;F_{HCl},F_{NaOH}) + (\omega_p)\, pH_p(k)}{\omega_m + \omega_p} \tag{3.18}$$

Where, for two models, the weight can be written as

$$\alpha = \frac{\omega_m}{\omega_m + \omega_p} \quad \text{and} \quad 1-\alpha = \frac{\omega_p}{\omega_m + \omega_p}$$

Thus, the hybrid model design can be seen as

$$\begin{aligned} pH_{h1}(k) &= pH_m(k;F_{HCl},F_{NaOH})(\alpha) + pH_p(k)(1-\alpha) \\ &= pH_m(k;F_{HCl},F_{NaOH})\frac{\omega_m}{\omega_m+\omega_p} + pH_p(k)\frac{\omega_p}{\omega_m+\omega_p} \end{aligned} \tag{3.18}$$

Weight (α) is proportion to each model to predict the output. As mention, the weight can be selected from a constant number or function. Figure 5 indicates the influence strength between mathematical and neuro-fuzzy model. The RMSE for hybrid model increased with increments of the weight (α). This correlation shows that the hybrid model is influenced by both models, which at nominal condition, neuro-fuzzy model gives better prediction (less RMSE), compared with the mathematical model (high RMSE).

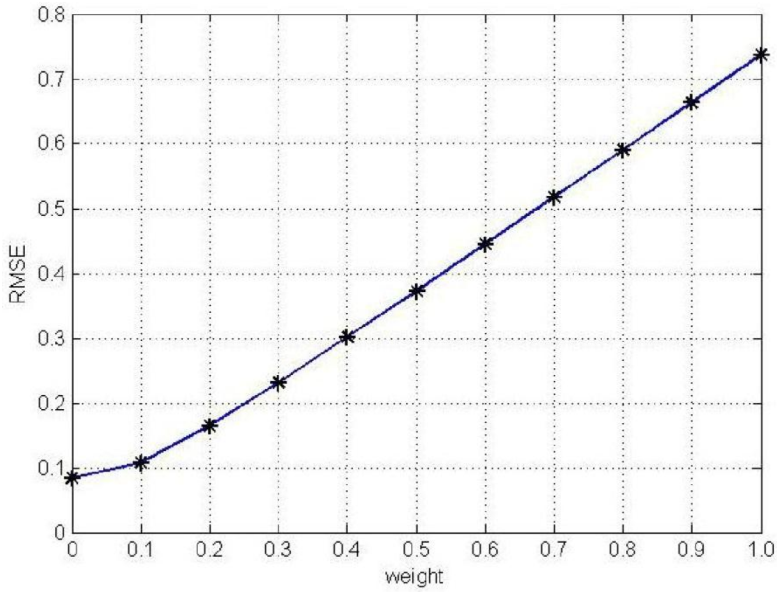


Figure 3.5: Hybrid model RMSE values with different weight selection

The weight (α) equal to zero means that the hybrid model is completely influenced by neuro-fuzzy model, while the weight when $pH_m(k; F_{HCl}, F_{NaOH})(0) + pH_p(k)(1-0)$ is equal to one means that the hybrid model is totally influenced by the mathematical model. These two cases give a correlation to decide the best weight at a particular time for hybrid model to achieve lowest RMSE. Thus, the weight is selected from time to time resulting in a dynamic weight profile. Eq. 3.19 is used to assign the dynamic weight as a function of absolute error from two models (Math and Neuro-fuzzy) since absolute error shows the magnitude of error deviated from the on-line dataset.

$$\alpha = f(|e_{math}|, |e_{ANFIS}|) = \begin{cases} \dfrac{\min(|e_{math}|, |e_{ANFIS}|)}{sum([|e_{math}| ; |e_{ANFIS}|])} & if\ |e_{math}| > |e_{ANFIS}| \\ \dfrac{max(|e_{math}| , |e_{ANFIS}|)}{sum([|e_{math}| ; |e_{ANFIS}|])} & otherwise, \end{cases} \quad (3.19)$$

As conclusion, the hybrid model predicts pH value based on performance of mathematical and neuro-fuzzy model. Selecting best weight from each model will give good prediction of hybrid model with lowest RMSE. In nominal working condition, the lowest weight is preferred since neuro-fuzzy model predicts better than mathematical model. However, when working at new condition, neuro-fuzzy may not perform well.

Then, a right weight, $\alpha \in [0,1]$ is used to compensate for the neuro-fuzzy limitation. Therefore, the dynamic weight (Eq.19) could select the appropriate weight, which calculates by deviation magnitude from on-line dataset with models output.

Chapter 4 : Controllers design for pH neutralization process

4.1 Conventional PID controller design

Conventional PID controller has standard mathematical expression. It is a combination of Proportional action, Integral action and Derivative action as in Eq. 4.1. As describe in Literature Review section as,

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{d}{dx} e(t) \tag{4.1}$$

The PID controller design has many methods to follow. This study used industrial practical method for controlling pH at 7. Since PID controller is only for linear processes, therefore the design configuration only works around pH 7.

The design is follows;

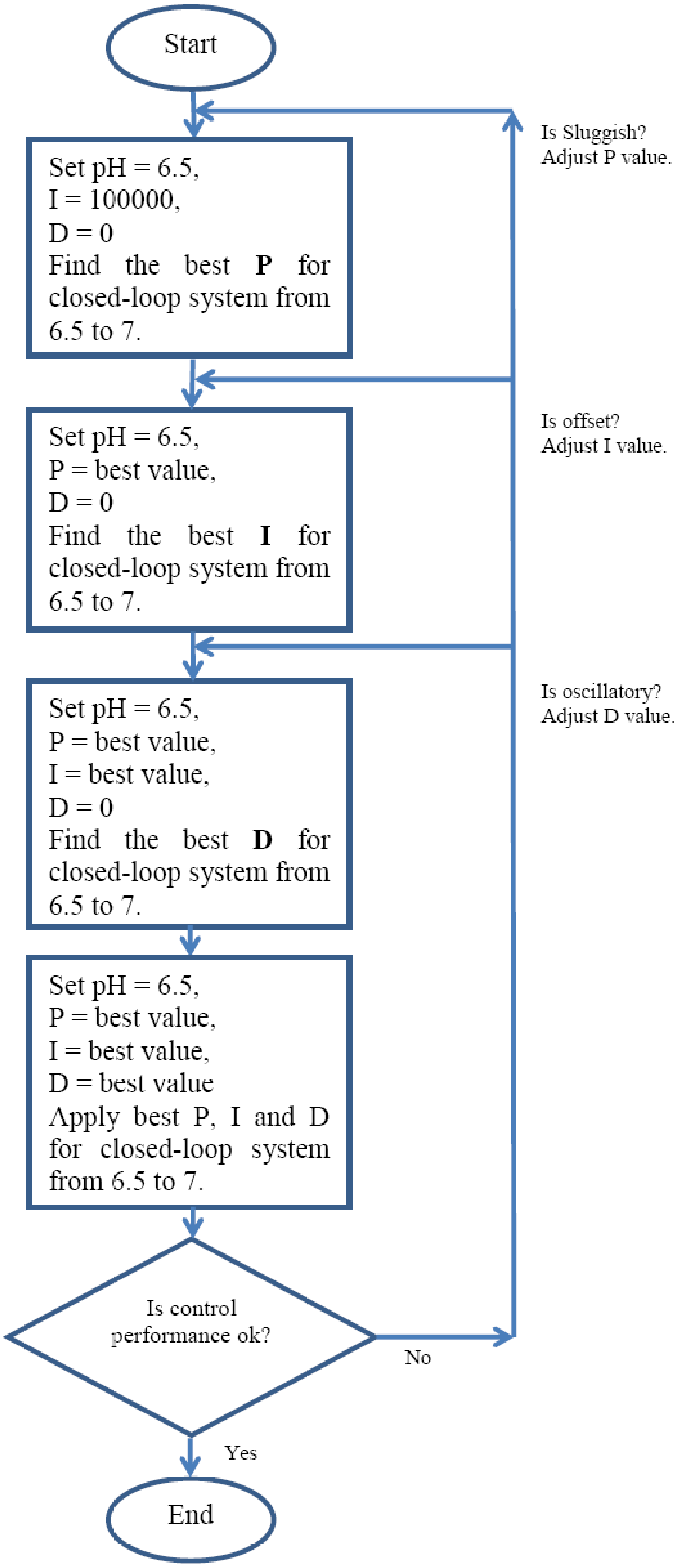


Figure 4.1: PID controller tuning

The PID controller has been tuned according to on-line control performance by using step in Figure 4.1. The tuning parameter can be obtained as in Table 4.1. The methodologies of conducting those controllers tuning are not described in details. One can found in many literatures about those tuning method.

Table 4.1: PID tuning parameters

PID controller	**P**	**I**	**D**
Try and error tuning	0.002	12	5
Ziegler-Nichole Tuning			
Cohen-coon Tuning			

4.2 Fuzzy logic controller design

Fuzzy Logic (Fuzzy Logic) controller design and analysis is discussed in this section. Fuzzy Logic Controller is described as a decision-making system that works in the linguistics framework. Fuzzy Logic was been introduced by (Zadeh, 1965), a founder of fuzzy set theory. In daily activities, fuzzy logic has been practised idea without realizing it. In conventional fuzzy system, fuzziness has average of 0 to 1. However, in Fuzzy Logic controller, it has ranges from 0 to 1 and it has systematic approaches that different from conventional fuzzy idea.

Fuzzy Logic system has a framework called fuzzy inference system (*fis*) based on Zadeh fuzzy set. It is a fuzzy methodology for mapping linguistic knowledge into fuzzy set systems. In Fuzzy Logic controller, *fis* framework is used to map input signal into linguistic labels such as “error”, “rate” etc. and evaluate output label depend to consequent action into crisp value know as control action. Fuzzy Logic system used human experience information, as knowledge regarding open loop characteristic on pH modelling from previous section.

4.2.1 Fuzzy Logic control strategy

Feedback control strategy is desired for all applications control system in this study. In feedback loop control (in Figure 4.2), error variable is normally used as a Fuzzy Logic input. This variable is an essential parameter for guiding the controller to achieve the desired set point. In theory, "error" is defined as difference between reference value, r(t) to process variable value, e(t) = r(t) – y(t).

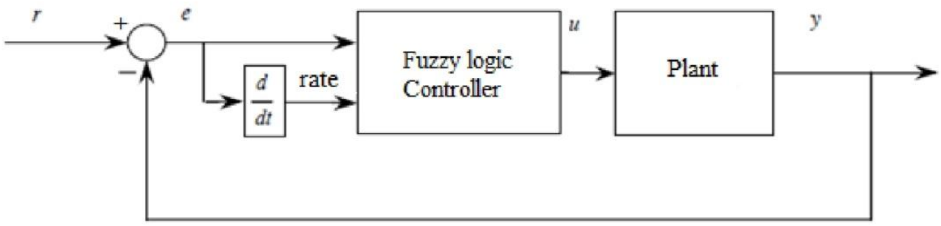


Figure 4.2: Feedback closed loop system with Fuzzy controller.

In addition, error could be extended into rate of error. Since human understand literally how fast error changes from certain point to another point, rate of error ("rate") is another state of Fuzzy Logic input that is interesting to study in the feedback control system. Label "rate" is defined as change of error in time, rate (t) = d/dt [e(t)]. It is also known as a gradient of error; either error is increasing or decreasing from previous state. Thus, these terminologies like "error "and "rate" are used in this strategy. Then, input label for the Fuzzy Logic controller is chosen as "error" and "rate".

While Fuzzy Logic controller output (u) can be from any state variables like current, voltage, flow rate, heat supplied and many more, but it should be related to manipulated variable in control system. The opening-valve as controller output (manipulated variables) is used since the opening is a function of flow rate in pH neutralization control system. In the pilot plant, opening-valve depends on voltage supplied into a valve transducer. It will convert the voltage to air pressure in psi. Range o to 10miliVolt is applied for 0% open to 100% open respectively. Therefore, voltage is selected as output state in Fuzzy Logic controller by using "valve" label.

4.2.2 Selection of input and output membership functions

Feedback control system is applied in this study, then “error” is the first item in Fuzzy Logic controller. The error signal is the same as input in PID controller and for Fuzzy Logic controller; error is mapped into linguistic variables like “zero”, “negative” and “positive” for minimal number of fuzzy membership. Three labels are sufficient to map all bounded error signal from control system. While second input is “rate”. It could be label as “increased”, “noChange” and “decreased” minimally. However, number of label (membership) in first input (error) and second input (rate) could be more that suggested number. It could give more computational load but smooth controller performance.

The output from Fuzzy Logic controller (“valve”) is divided into 5 labels (membership) which is “closed”, “smallOpen”, “midOpen”, “largeOpen”and “FullOpen”. It is because flow rate value (litre/min) between each labels (example: “closed” and “smallOpen”) has almost no significant difference.

Design of Fuzzy Logic controller is begun by letting data set, A_i and crisp value, x_i (“error”, “rate” and “valve”) into control system. In classical mathematical form, it might be expressed as:

$A_{error} = (x_{error} \mid -1< x_{error} < 1)$, $A_{rate} = (x_{rate} \mid -1< x_{rate} < 1)$ and $A_{valve} = (x_{valve} \mid 0< x_{valve} < 10)$.

However, in fuzzy inference system, data set A_i has an extension to classical data set which includes each crisp value x_i into MF equations for all elements in A_i. This membership function equations map each element in X_i (X_i is crisp value for all ranges in MF) into membership value between 0 and 1 as shown below:

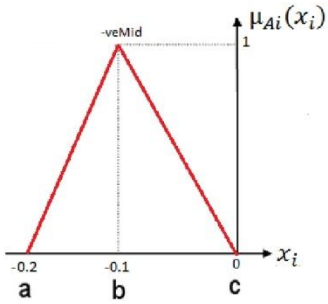
$A_{error} = (x_{error}, \mu_{Aerror} (x_{error}) \mid x_{error} \in X_{error})$

$A_{rate} = (_{xrate,}\ \mu_{Arate} (x_{rate}) \mid x_{rate} \in X_{rate})$ and

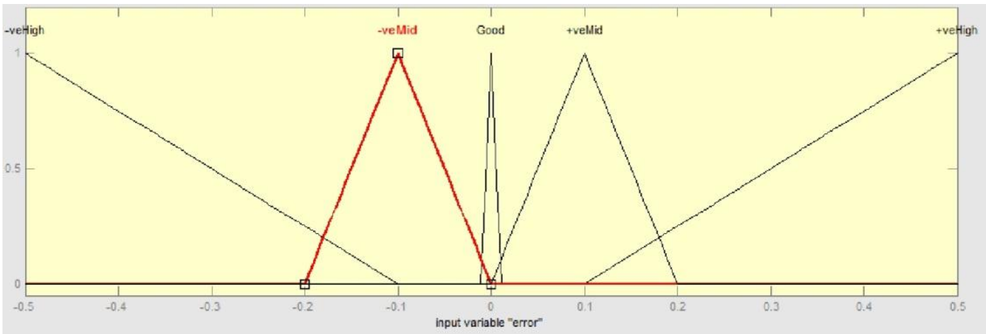
$A_{valve} {}^{=} (x_{valve}, \mu_{Avalve} (x_{valve}) \mid x_{valve} \in X_{valve})$.

where μ_{Ai} is MF equation of label represented by a geometrical shape. As initial design, triangular shape as input MF is used to convert crisp input value by using function below (μ_{Aerror} (x_{error}),μ_{Arate} (x_{rate})):

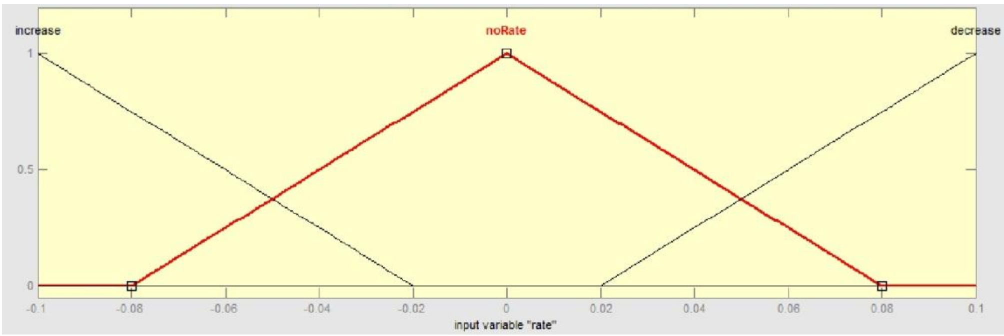
$$\mu_{Ai}(x_i) = \begin{cases} 0 & if\ x_i \le a \\ \dfrac{x_i - a}{b - a} & if\ a \le x_i \le b \\ \dfrac{c - x_i}{c - b} & if\ b \le x_i \le c \\ 0 & if\ x_i \ge c \end{cases}$$



Where a, b, c is triangular shape parameters and *i* denote as “error” and “rate”. All graphical MF shape and parameter for inputs variable can be obtained below (Figure 4.3 and Table 4.2) respectively. Triangular shape is favoured initially, because it easy to construct and gives good performance.



(a)



(b)

Figure 4.3: Graphical illustration of inputs membership function;
(a) input variable “error” (b) input variable “rate”

Table 4.2: MF input variables parameter and values.

Name	i = "error"				i = "rate"			
Range	Min: -0.5; Max: 0.5				Min: -0.1; Max: 0.1			
No	**Name**	**a**	**b**	**c**	**Name**	**a**	**b**	**c**
1	-veHigh	-0.8	-0.5	-0.1	increase	-0.18	-0.1	-0.02
2	-veMid	-0.2	-0.1	0	noChange	-0.08	0	0.08
3	Zero	-0.01	0	0.01	decrease	0.02	0.1	0.18
4	+veMid	0	0.1	0.2				
5	+veHigh	0.2	0.5	0.8				

Input "error" contains 5 MF functions where "-veHigh" and "+veHigh" are catered to cover up error value if pH values reference change from 6 to 8 or vice versa. "-veMid" and "+veMid" is for converting error value in small scale. While at "Zero" label, the controller output value should be maintained because the crisp value at moment shows that the Fuzzy Logic controller has achieved the control objective. On the other hand, only 3 MF are required for input "rate". It is minimal number of action since basic rate can be either increase, decrease or no change.

Figure 4.4 shows the procedure to design the MF as described above.

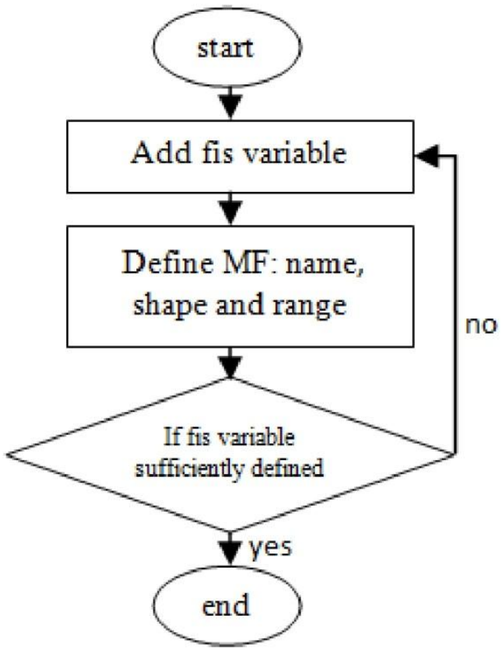
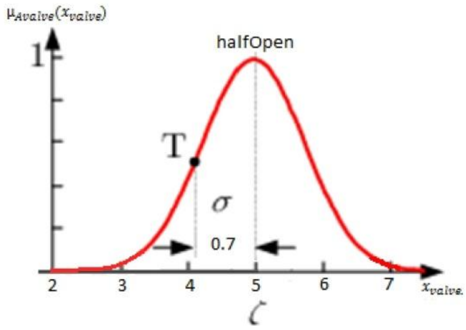


Figure 4.4: Membership function design procedure

4.2.3 Mamdani's fuzzy inference system design

As described previously (Section 4.2.2), Mamdani's output membership function is different compared to Sugeno's type. As a starting point, Gaussian shape is chosen as output membership function, $\mu_{Avalve}(x_{valve})$ for Fuzzy Logic controller because Gaussian shape inherits nonlinear behaviour compared to triangular shape. It can be described as follows:

$$\mu_{Avalve}(x_{valve}) = e^{-\frac{(x_{valve}-\zeta)^2}{2\sigma^2}}$$



Where σ and ζ are Gaussian shape constant, which can be found in Table 4.3, and is illustrated as in Figure 4.5. Gaussian shape is selected because this equation provides smooth transition response to control valve.

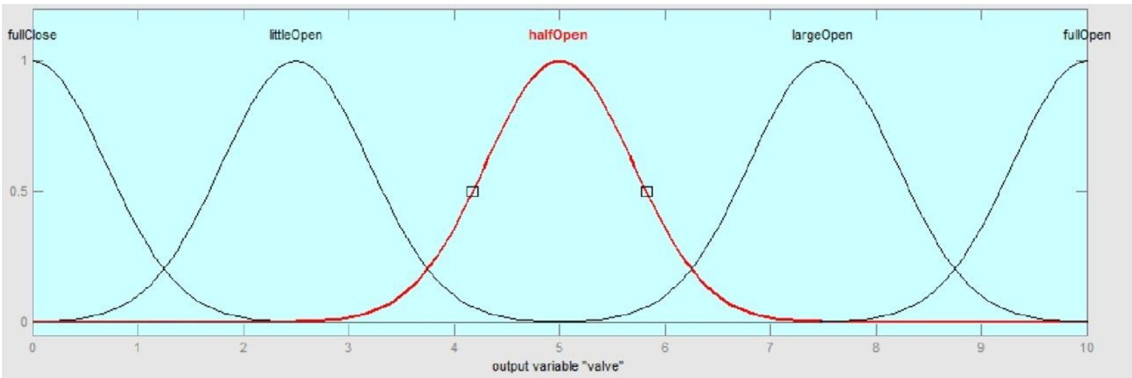


Figure 4.5: Graphical illustration of output membership function "valve"

Table 4.3: Mamdani's output MF: variables parameter and values.

Name	**"valve"**		
Range	Min: 0; Max: 10		
No	**Name**	**σ**	**ζ**
1	fullClose	0.7	0
2	littleOpen	0.7	2.5
3	halfOpen	0.7	5.0
4	largeOpen	0.7	7.5
5	fullOpen	0.7	10

In pH neutralization control case study, the final element of the control system is control valve and it ranges between 0 to 10 millivolt crisp inputs value. As in a real-plant, interval of 2 millivolt is significant opening different for base flow rate to take action. For instance, 2.1milivolt has no significant change in base flow rate compared to 4milivolt. The next step for Fuzzy Logic controller design is to construct the control command rules based on input and output MF defined earlier. Fuzzy rules for Mamdani's inference system are:

Rule 1: *If "error" is -veHigh AND "rate" is increase then "valve" is fullClose*
Rule 2: *If "error" is zero AND "rate" is increase then "valve" is halfOpen*
Rule 3: *If "error" is +veHigh AND "rate" is increase then "valve" is fullOpen*
Rule 4: *If "error" is -veHigh AND "rate" is decrease then "valve" is fullClose*
Rule 5: *If "error" is zero AND "rate" is decrease then "valve" is halfOpen*
Rule 6: *If "error" is +veHigh AND "rate" is decrease then "valve" is fullOpen*
Rule 7: *If "error" is -veHigh AND "rate" is noChange then "valve" is fullClose*
Rule 8: *If "error" is zero AND "rate" is noChange then "valve" is halfOpen*
Rule 9: *If "error" is +veHigh AND "rate" is noChange then "valve" is fullOpen*

In the list of fuzzy rules above, Rule #8 is the most important since it guaranties the Fuzzy Logic controller to meet the desired control objective. Determination of the fuzzy rules can be hard for a new plant but it is easy for an established plant since stationary state and dynamic response of the plant are available during plant operation. At the pilot plant, to achieve stationary state (error is zero and rate in not change), flow rate of NaOH must be the same as HCl flow rate, since both concentration is the same at feed storage tank. Rule #8 only caters at stationary state with maintain reference and process variable value.

The rest of fuzzy rules listed above is to drive the process variable (pH) to the desired reference point. It has two conditions when process variable is below (error is positive) and above (error is negative) reference value. When error is positive, the mixing tank requires more NaOH so the action is to increase the opening valve. Another case when error is negative, the valve opening has to reduce in order to lessen the pH value in tank.

4.2.4 Sugeno's fuzzy inference system design

The designed fuzzy inference system for Sugenno's method is described in this sub-section. As continuity from the previous Fuzzy Logic controller design, there are no changes in input and output definition. As mentioned (Section 4.2.2), Sugenno's fuzzy inference for output membership functions has a different approached. Recall that, Fuzzy Logic controller has five output labels, "closed", "smallOpen", "midOpen", "largeOpen"and "FullOpen". In Mamdani's fuzzy inference, those labels are represented by geometrical functions. For simplicity, a constant value is used for Sugeno's fuzzy inference instead of mathematical equations. In this study, the designed parameter for Sugenno's type fuzzy inference can be found in Table 4.4 below.

Table 4.4: Sugeno's output MF: variable parameters and values.

Name	**"valve"**	
Range	Min: 0; Max: 10	
No	**Name**	**Value**
1	fullClose	0
2	littleOpen	2.5
3	halfOpen	5.0
4	largeOpen	7.5
5	fullOpen	10

Next step after membership design is constructing the fuzzy rule base. Since Mamdani's inference has been designed earlier and the process is same, thus the relation for rule before can be used to complete the fuzzy inference design for Sugenno's type. The rules are:

Rule 1: *If "error" is -veHigh AND "rate" is increase then "valve" is 0.0*
Rule 2: *If "error" is zero AND "rate" is increase then "valve" is 5.0*
Rule 3: *If "error" is +veHigh AND "rate" is increase then "valve" is 7.5*
Rule 4: *If "error" is -veHigh AND "rate" is decrease then "valve" is 0.0*
Rule 5: *If "error" is zero AND "rate" is decrease then "valve" is 5.0*
Rule 6: *If "error" is +veHigh AND "rate" is decrease then "valve" is 10.0*
Rule 7: *If "error" is -veHigh AND "rate" is noChange then "valve" is 0.0*
Rule 8: *If "error" is zero AND "rate" is noChange then "valve" is 5.0*
Rule 9: *If "error" is +veHigh AND "rate" is noChange then "valve" is 10.0*

4.3 Fuzzy Logic controller with ANFIS Model

4.3.1 ANFIS model design consideration

The motive to implement ANFIS in control system is to increase the quality of Fuzzy Logic controller.

It can be achieved by using a hybrid technique between model identification and Fuzzy Logic controller. The inverse mathematical model and inverse ANFIS model is used.

The interaction between these two techniques is auxiliary hybrid (as in Literature review chapter Section 2.3.4). In this hybrid, the primary technique (Fuzzy Logic controller) works to produce control-action by using sub-solution from secondary technique (inverse ANFIS model). The Fuzzy Logic controller is extended by adjusting the output membership function with sub-solution from inverse ANFIS model. Figure 4.6 shows the close-loop block diagram where inversed hybrid model is supplying the suggested control action to the Fuzzy Logic controller.

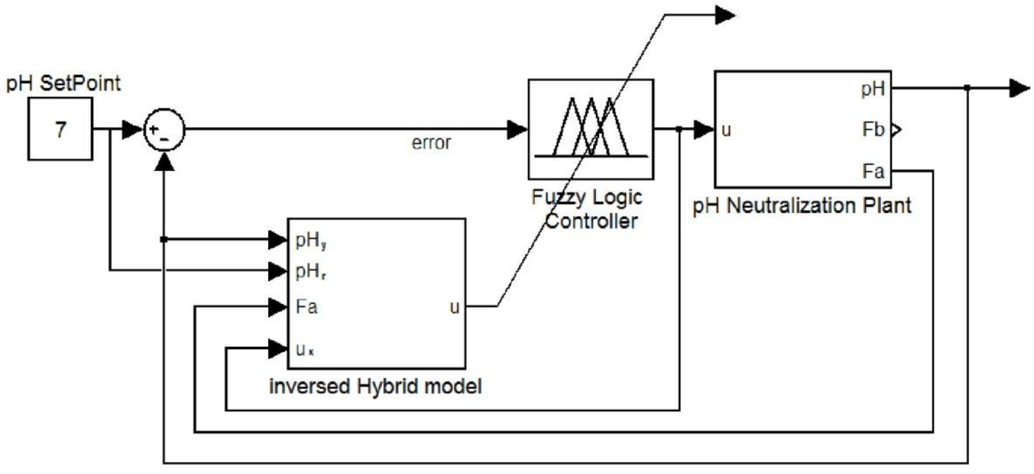


Figure 4.6: Proposed controller in feedback control of pH neutralization plant

4.3.2 Inverse ANFIS model design

Fuzzy Logic with combination of ANFIS is an attractive technique to model pH neutralization. It is because it provides a multi-model framework for modelling nonlinear behaviour at different pH neutralization regions.

This subsection is an extended step after ANFIS model identification as described at previous sub-section. The inverse ANFIS model is designed by using same input-output dataset as in model identification. However, input and output orientation in the dataset is inversed where the input is pH value and the output is control action. As a result, ANFIS produces an inverse behaviour of titration curve.

ANFIS training procedure is carried out as usual in ANFIS model identification. The ANFIS architecture with three inputs and one output is desired to cover control action dynamics during process control. The inputs are pH values at two different delays and previous control action at time b is another input variable. While, the output of this inversed ANFIS model is a predicted control action in millivolt.

Three input groups are chosen for ANFIS model which group no. 1 and 2 are for previous output value, y(t-1), y(t-2),y(t-3) and y(t-4) and input no 3 is for control valve input signal u(t-1), u(t-2), u(t-3) to u(t-6). After input is identified, 10 input candidates are trained and checked by comparing selected delays with input-output dataset for three iterations and best-fit RMSE for three inputs are known. Delay selection of inputs is based on lowest root mean square error (RMSE) within three input groups as shown in Figure 4.7.

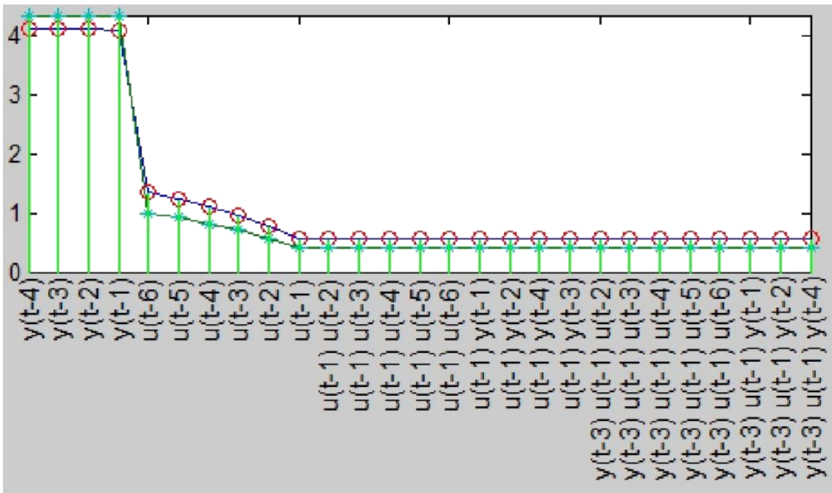


Figure 4.7: Sequential input selection

Selected inputs are y(t-1), y(t-3), u(t-1) with RMSE training = 0.2255 and RMSE checking = 0.2729. Inversed ANFIS model as shown in Figure 4.8 has five components consisting of three input variables, two membership functions in each variable, and eight unique possible combinations of fuzzy rules, consequent output equation, and output variable.

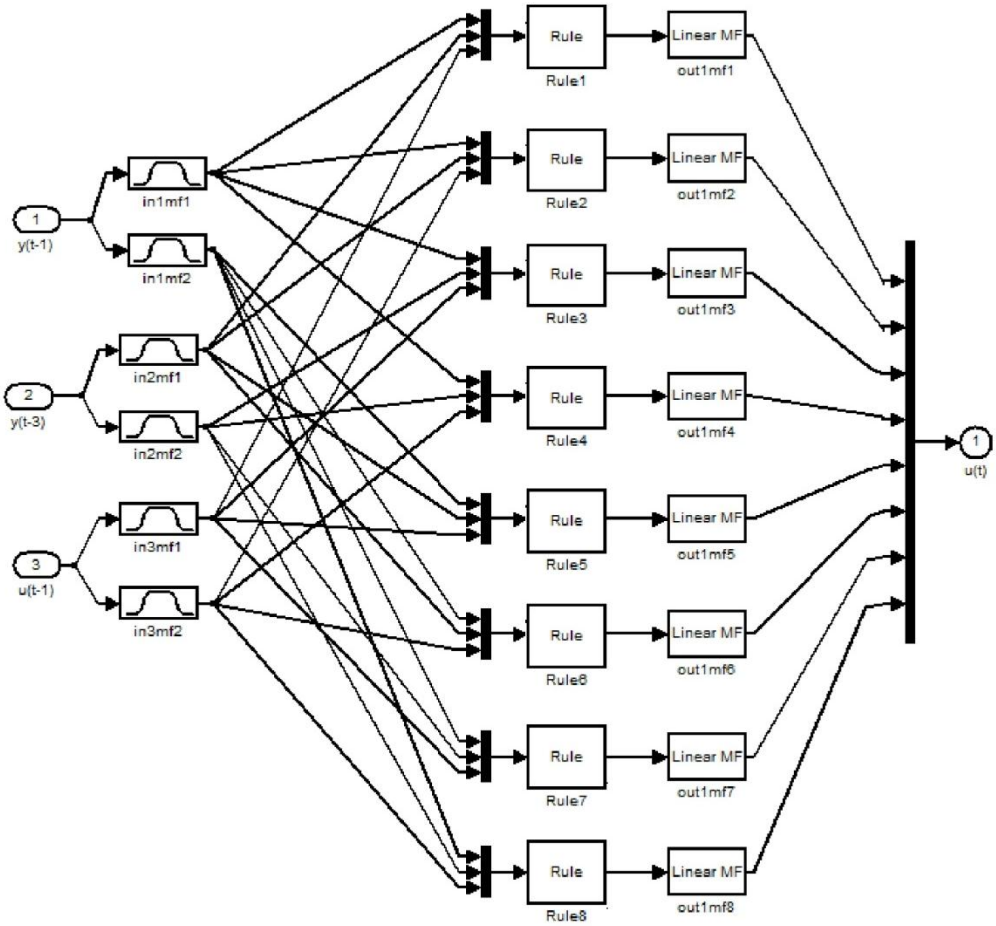


Figure 4.8: inverse ANFIS model structure

4.3.3 Inverse hybrid model design

The design used a combination of inversed model from first principle and ANFIS. Hybrid structure below is in a parallel configuration which is known as embedded hybrid as shown in Figure 4.9. The inversed ANFIS model is used to estimate control action for a pH value of real plant and inversed pH model is for calculation of control action of pH value as theoretical basis. ANFIS has capabilities to replicate the dynamics of inverse pH plant. By introducing mathematical model parallel to the ANFIS, the inversed model will be more robust in choosing different acid flow rate during offline/online process control investigation. Furthermore, additional variations like concentration of acid/base and reactor volume could be captured in the proposed controller.

On the other hand, hybrid weight α is introduced for managing output contribution of each model. The range of 0 to 1 for α is used to determine which model contributes more to the hybrid model. A key success to this model depends on ANFIS prediction value and hybrid weight, α, parameter as described.

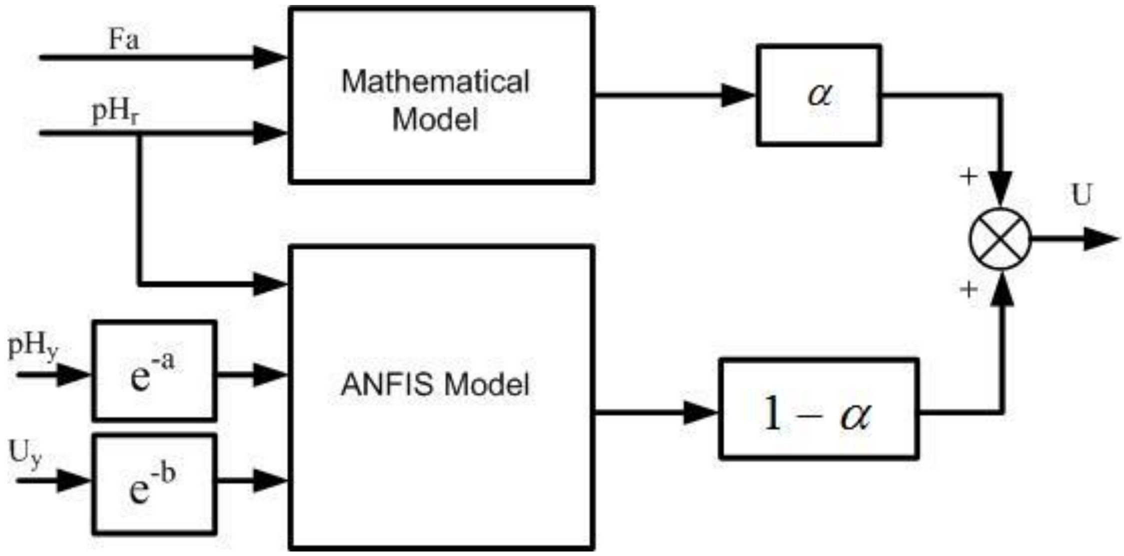


Figure 4.9: Inversed hybrid model structure

4.3.4 Hybrid Fuzzy Logic Controller design

Intelligent controller that is being proposed in this study composed of hybrid inversed model and Sugeno's Fuzzy Logic controller as shown in Figure 4.10. Auxiliary hybrid is used to combine both techniques to produce a hybrid intelligent controller that has ability to adapt and react within allowable plant modification and disturbance.

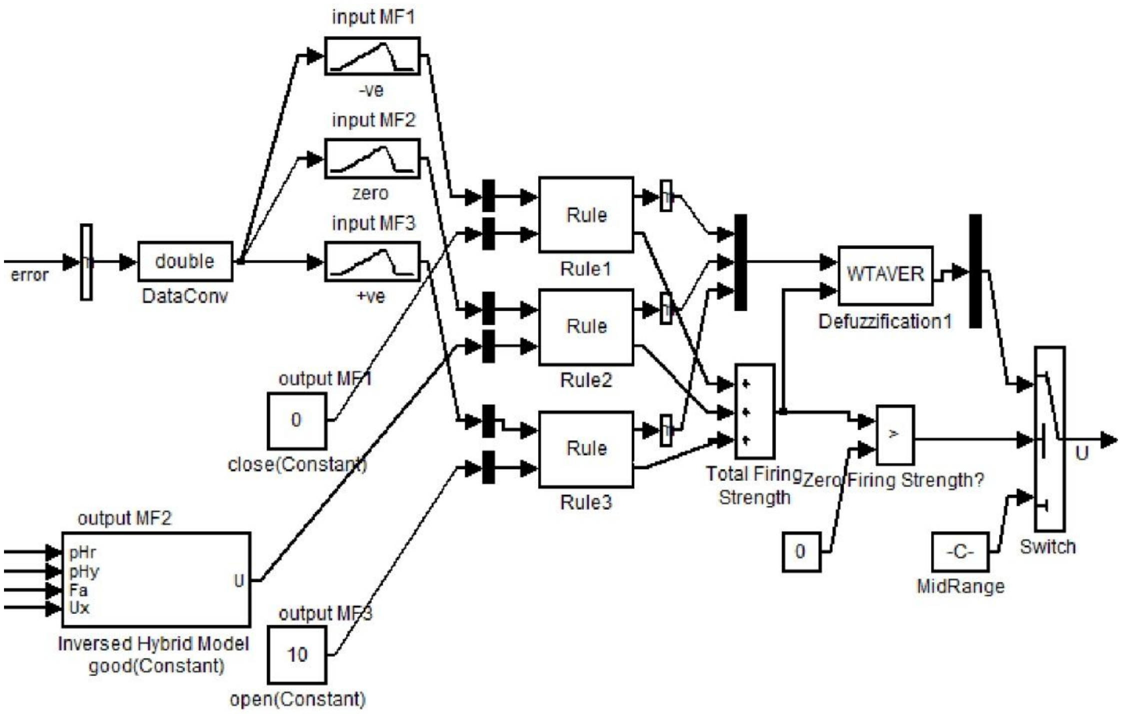


Figure 4.10: Proposed hybrid controller block diagram

Sugeno's Fuzzy Logic controller used in this study consists of one input and one output system. Input membership has three membership functions, which is a minimum membership function that can be used for feedback loop control strategy.

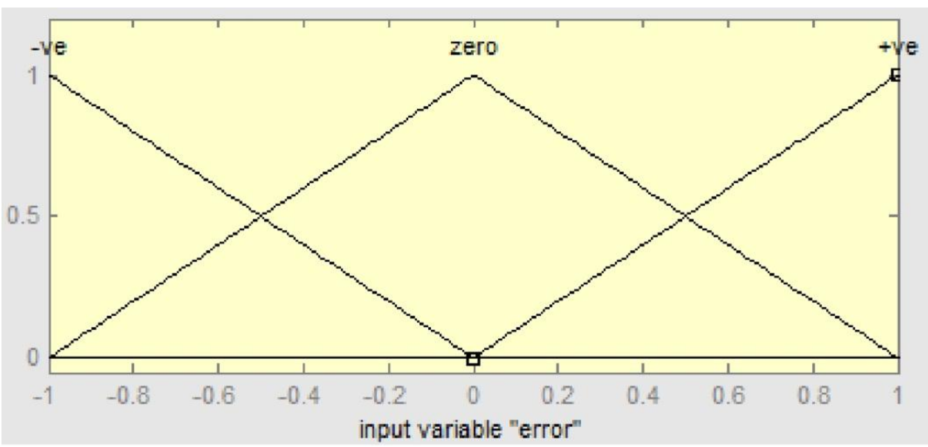


Figure 4.11: FLC Input membership functions

Figure 4.11 shows the input MF (error) label and value used in Sugeno's Fuzzy Logic controller while, output variable is a constant value and is labelled as "open", "good" and "close" respectively. Open and close can easily be selected since it a boundary of control action. However, "good" condition depends on steady state of the process when error is zero. Hybrid inversed model is acted would give a prediction of "good" value at particular time within a specific control system conditions.

Chapter 5 : The pH neutralization experimental setup

5.1 Control System Setup

5.1.1 Pilot plant design consideration

A good pilot plant design is important to achieve good control performance. In pH neutralization, to reduce time delay is important since this would create instability in model and control system. The time delay may be present at process time delay (tank size), delivery of reagent (acid and base), and measurement device (at pH electrode). These delays can be minimized if pilot plant is designed properly.

Another importance issue is sensitivity of the final-element (control valve). This is because at neutralization region it needs a very small control action that require small amount of reagent to pass through control valve. The proper control valve selection during pilot plant design could give better quality of control performance.

Next, the environmental issue regarding the pilot plant effluent. The effluent from this plant must be treated before it passes through to public drain.

5.1.2 pH neutralization pilot plant

The neutralization pilot plant is located at Chemical Engineering Department, University of Malaya. Figure 5.1, show process, and instrument diagram which illustrate the experimental setup.

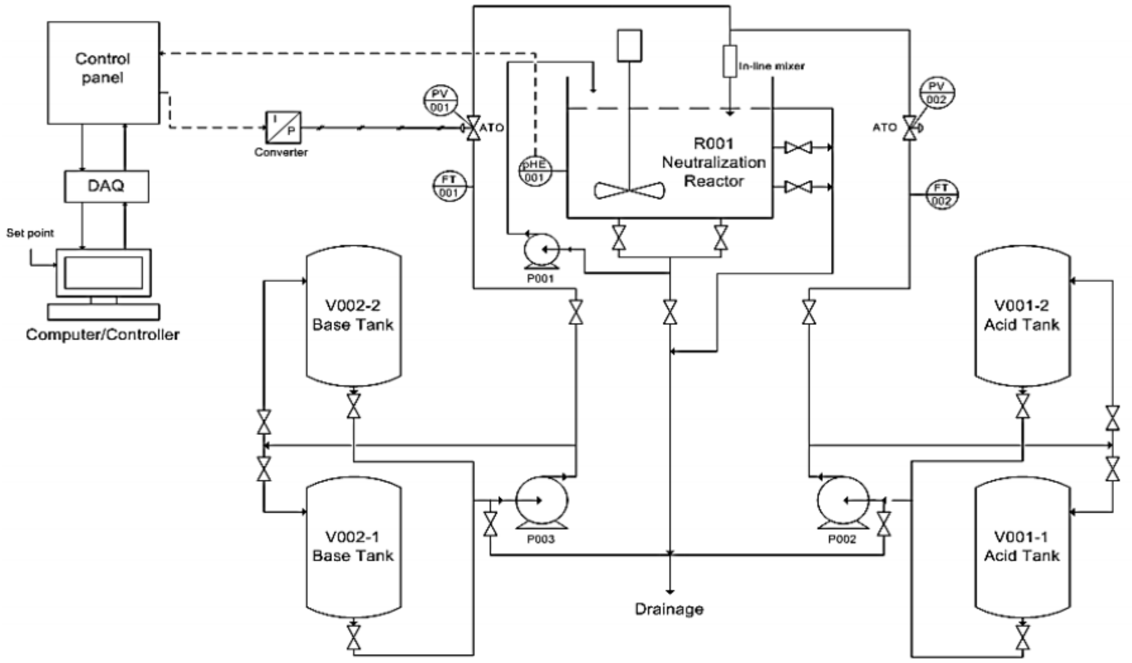


Figure 5.1: Process and instrumentation diagram for pH neutralization

It has 500-liter holdup capacity in mixing a rector and 200-liter initial feed supply for acid and base (Figure 5.2).

Figure 5.2: Pilot plant for pH neutralization

The mixing tank design and layout is important as described in Figure 5.1. Our tank has two inlets flow and four outlets located in the tank. The mixing tank has a recycle stream which provides a well-mix solution. The outlets stream is mainly to the discharge the mixture in the tank. One located at the bottom of the tank for maintenances purpose while the rest located at the side of the reactor vertically. The height of holdup volume in the reactor is depending on the vertical outlet. The outlets diameter is much bigger than the inlet diameter so it can guaranty that the height is always constant at desired level.

The experiment used 100-liter as a holdup volume. It is desired at this level since the recommendation to have a good mixing condition is when liquid depth is equal to tank diameter. The reason is to minimize the traveling distant for reagents from the inlet. The retention time for 100-liter is 7 min that is calculated from volume divided by the flow rate. In normal practice for liquid-liquid reaction without solid formation, the retention time (dead time) is from 5 to 20 minutes (McMillan & Cameron, 2005).

The high-speed axial mixing propeller is used at 25 rads per minute (rpm). It is to reduce the dead time effect and enough to break the fluid inside the tank. So that the reagent goes to the bottom of the tank since the pH electrode is located at the bottom of the tank. The dead time t_d, is 0.32min gained from holdup volume divided by the summation of inlet flow rate and agitator pumping capacity as shown below.

Table 5.1: Mixing tank details

Parameter	**Value**	**Unit**
Diameter	100	cm
Height	500	cm
Impeller speed	25	RPM
Impeller diameter	9	cm
Baffle	4	
Impeller	3 blades butterfly type	
Flow rate	9 - 14	Litre/min

At the tank, static mixer (Figure 5.3) is installed. The purpose of this mixer is to reduce dead time delay caused resident time distribution. In literature, the static mixture reduces 80% of resident time (McMillan & Cameron, 2005).

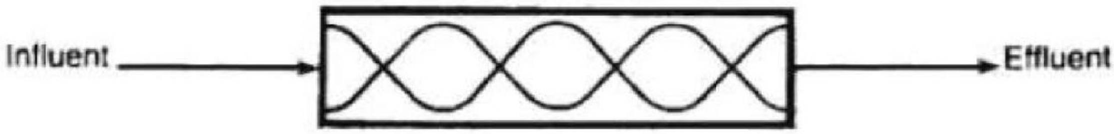


Figure 5.3: Static mixture for acid and base before entering the reactor

5.1.3 pH sensor

The pH value is measured by pH electrode. The pH value is obtained when pH-sensitive glass having contact with the aqueous solution. Nerst equation is used to calculate the potential energy generated from the exchange of hydrogen ion (proton) between hydronium ions in aqueous solutions.

The pH electrode used is from EUTECH instrument hardware. It is located at the bottom of the reactor tank. As in Figure 5.4, pH value is obtained inside the mixing solution, which reduced transportation lag.

Figure 5.4: pH transmitter used in the pilot plant

The sensor location is important for pH neutralization control system. It should be located at most representative, reliable, and fastest measurement. In our experimental setup, it is located at close to the exit pipe line of the mixing reactor. In this case, the pH electrode can measure the pH value and the reagent has sufficient time to completely mix before discharge so that it will increase the controller and model performance.

5.1.4 Control valve

The range-ability for final element is most importance. It determines the controller performance since pH neutralization has non-sensitive and sensitive control action. In literature for normal strong acid and base, metering pump should in ratio 20:1 to 200:1 for control action over flow rate (McMillan & Cameron, 2005). In addition, linear valve characteristic is preferred and using smart digital positioner is recommended.

Figure 5.5: Control valves (acid and base) used in the pilot plant

In the experiment, two units of control valve are used as in Figure 5.5. Both control valves used is pneumatic type, which require air to open and to close. The transducer is located near the control valve to convert the control action from millivolt to psig.

5.1.4 Control system

The set point change is important. The pH response depends on the regions in titration curve. Local linear behaviour would be expected if the set point at the flat portion of the regions. However, the nonlinear controller must be used if the set point is located at two different regions due to sensitive and non-sensitive control action.

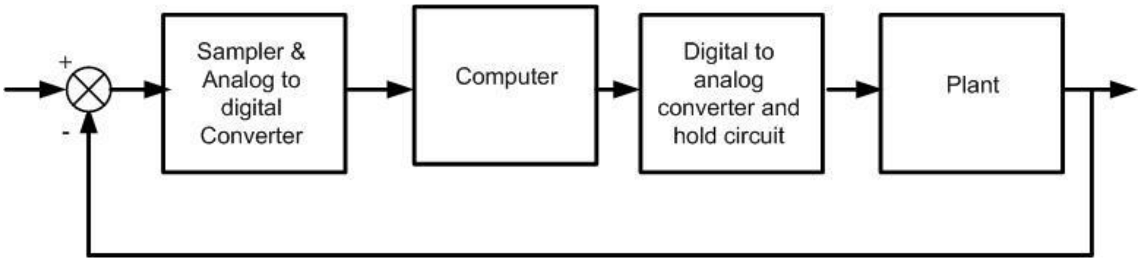


Figure 5.6: Closed-loop structure for on-line study

The tracking specifications depend on process plant requirement as in Table 5.2.

Table 5.2: Control objectives for set-point tracking regions

pH neutralization region	Process variable	Tracking range
Acid	pH	4.5 to 6.5
Neutralization	pH	6.5 to 7.5
Base	pH	7.5 to 10.5

As in Table 5.2 above, pH neutralization control system, range between 6.5 and 7.5 is desired since neutralization point is within this range.

The controller in feedback control system is to reduce error between plant and reference value. Figure 5.7 below shows a control system strategy used in this study.

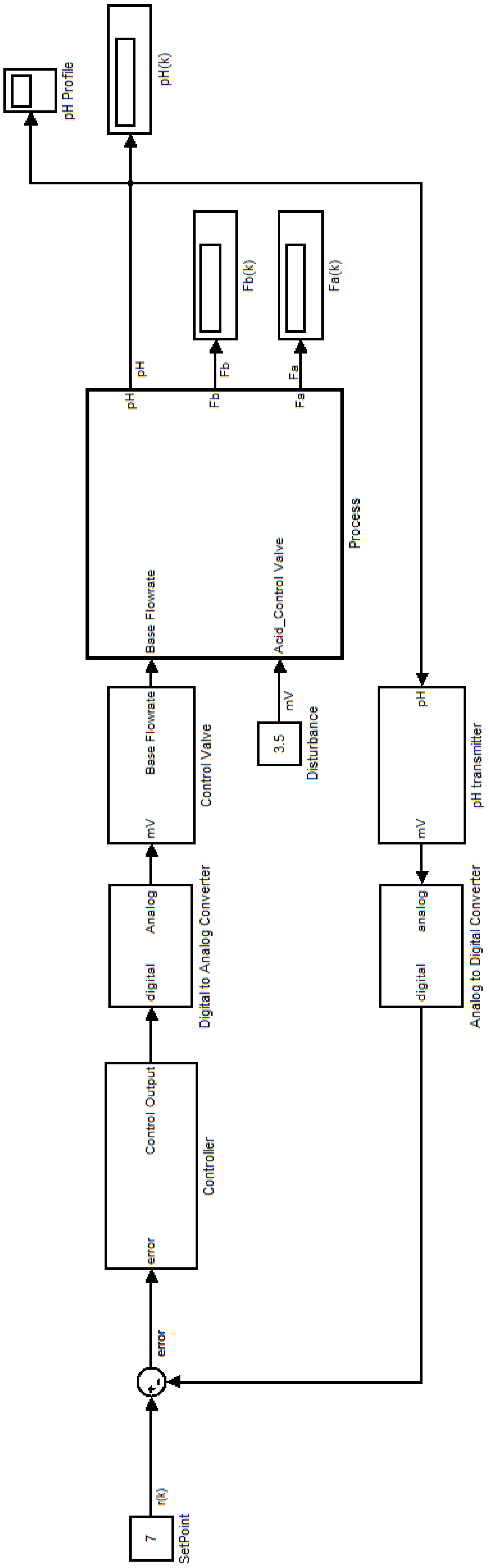


Figure 5.7: Structure of closed-loop block diagram for on-line pH neutralization system

5.2 Experimental work procedures

5.2.1 Open loop study

The focus of this section is to describe the steps that being carried out in open loop experiment. The dynamic profile of neutralization can be obtained through these steps. The experiment starts with preparing the feed tank as in nominal operating condition (Refer Table 3.1). At this step, there are no flows for both input streams. It can be done by sending 0 milivolt to the control valves through control system user interface. On the other hand, the mixing reactor has to be maintained at 25 rpm agitation speed and recycle pump is switching on. The open loop study should begin with pH value of 3 (same pH value as in HCL feed tank) and it end at pH of 11 (same pH value as in NaOH feed tank).

Next, open the HCL stream line control valve about 10% opening. This valve will give the mixing reactor in acid condition. After sometime, gives step change input of 0 to 100% opening to NaOH stream line control valve. This step will increase the pH value in mixing reactor. Observe and monitor the pH changes by plotting a real time signal by using software interface in computer. The open loop study finish when pH value in reactor saturated.

This open loop procedure has to be repeated at different input step change according to objective of the investigation. The need to repeat this procedure is must if the data is used as a training dataset in modelling identification.

5.2.2 Closed loop study

As discussed previously, closed loop study is a feedback control system. It has a complete control system block and it objective is to bring the present value to a desire set-point value. The objective can be achieved by design the controller appropriately according to the pH neutralization plant condition and control strategy used.

The procedure in this section can be used for a several closed loop control system investigations which is carried out in this research. At preliminary step, the plant should be in a close loop mode and plant condition should be at nominal condition (refer Table 3.1). This step can be checked by verifying the signal at the control panel with the computer interface. Firstly, bring the mixing reactor at saturation pH value by setting a set-point block at user interface. Next, the study performs a controller investigation like servo (set-point change) and regulatory (disturbance rejection) case study.

For servo case, acid stream line control valve should be maintained as in Table 3.1. The reason is because, for a servo case, we need to see the effect of set-point change only and by maintaining the flow rate of acid, the deviation of disturbance is equal to zero. The servo case starts with several set-point changes as described earlier.

For regulatory case, it start when pH value for the mixing reactor at saturation. The disturbance should be introduced at this state. In this study, the disturbance can be introduced by changing the acid flow rates differ from the nominal condition.

This study ended by obtains the real-time profiles.

Chapter 6 : Result and Discussion

6.1 Models validation

6.1.1 Mathematical model

The mathematical model derived gives "s-shape" curve, which is determined by logarithm function. In Figure 6.1, the designed mathematical model produced a characteristic of pH neutralization. It shows the model is nonlinear with several dynamic regions. At first region (pH < 6), slow response is observed while very fast response at second region (6<pH<8). At third region, slow response is detected and the pH is saturated at pH 9.6.

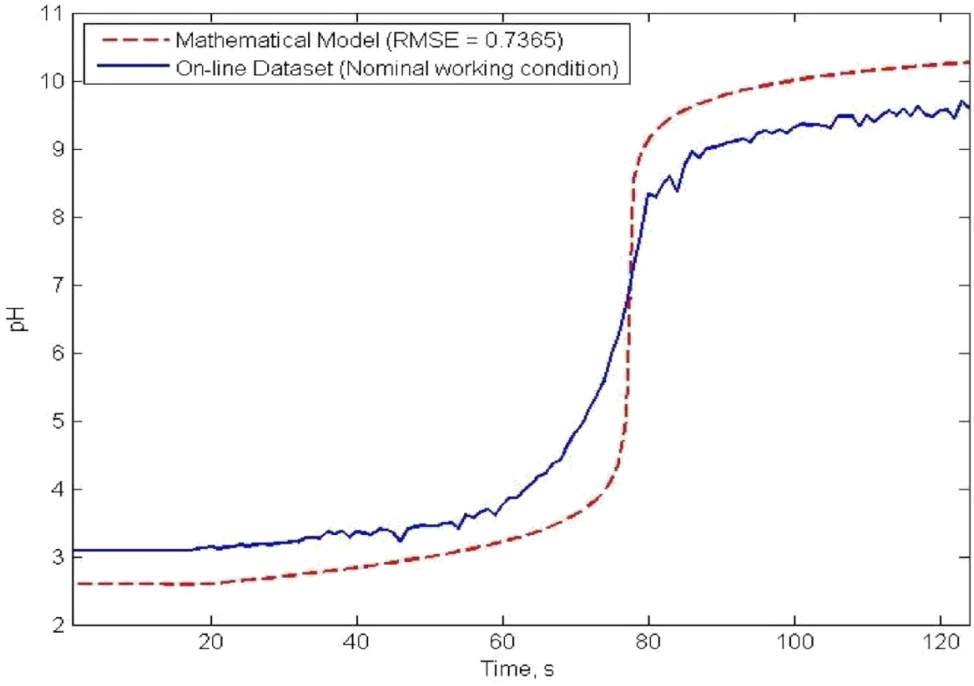


Figure 6.1: Mathematical model profile of pH neutralization (RMSE = 0.7365)

The profile draws a theoretical boundary along the titration curve (same dataset as in neuro-fuzzy model). Figure 6.1 shows that the mathematical model is able to give pH value with RMSE = 0.7365. The model using on-line data (signal from acid-base flow rate) is fed into the model equation. The deviation of theoretical profile with real experimental profile maybe cause of the assumption made in theory development. It shows an offset but it enough to show the profile is in sigmoidal curve which is basic theory of strong acid and strong base neutralization.

6.1.2 ANFIS model

The on-line dataset was obtained by fixing the acid flow rate at (5.0 ± 0.1) litre/min and introducing a step change from (0 to 13.0±0.1) litre/min flow rate for the base in input flow rate. The signal was channelled to the fuzzy logic block, which contained the ANFIS configuration, and the pH profile was recorded. At nominal working condition, neuro-fuzzy model gives best prediction for on-line dataset with RMSE = 0.0833. It indicates that the model is capable to predict the pH value if same condition is used as in ANFIS training. Figure 6.2 shows that the neuro-fuzzy model is held at trained condition.

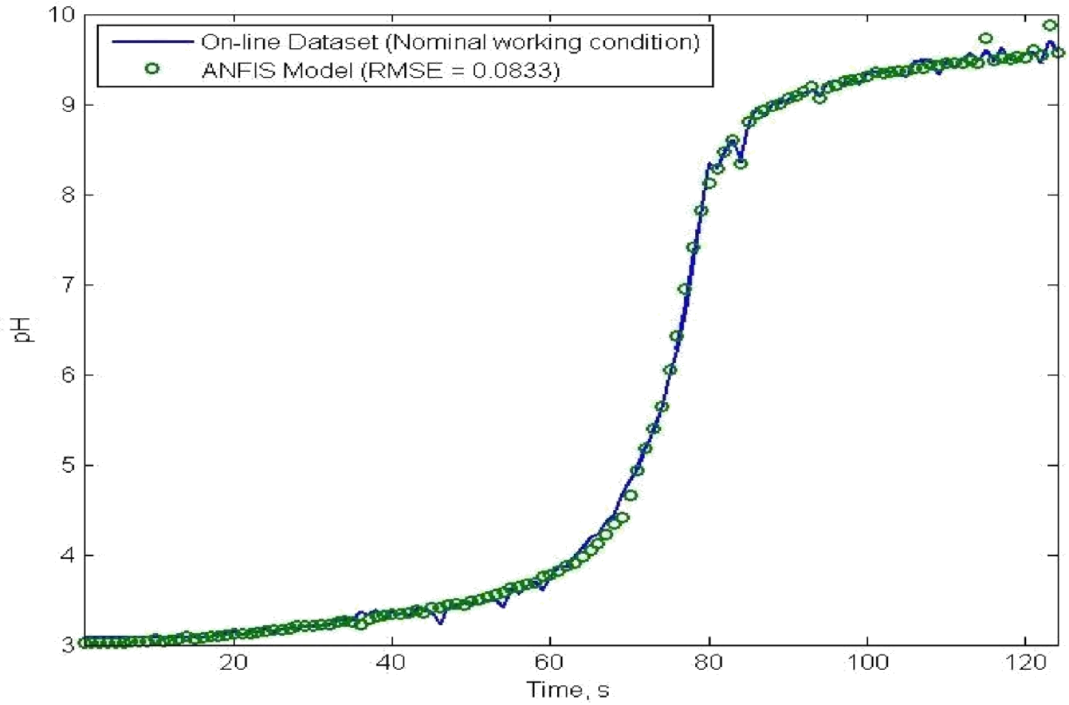


Figure 6.2: Comparison Training Dataset with ANFIS prediction (RMSE = 0.0833)

6.1.3 Hybrid model and comparative analysis

By using both model output predictions, the hybrid model is implemented by taking the weight with an initial value of 0.6. This shows that the hybrid model has a 40% influence from neuro-fuzzy model and 60% from mathematical model and gives a

RMSE of 0.4446 (Figure 6.3).

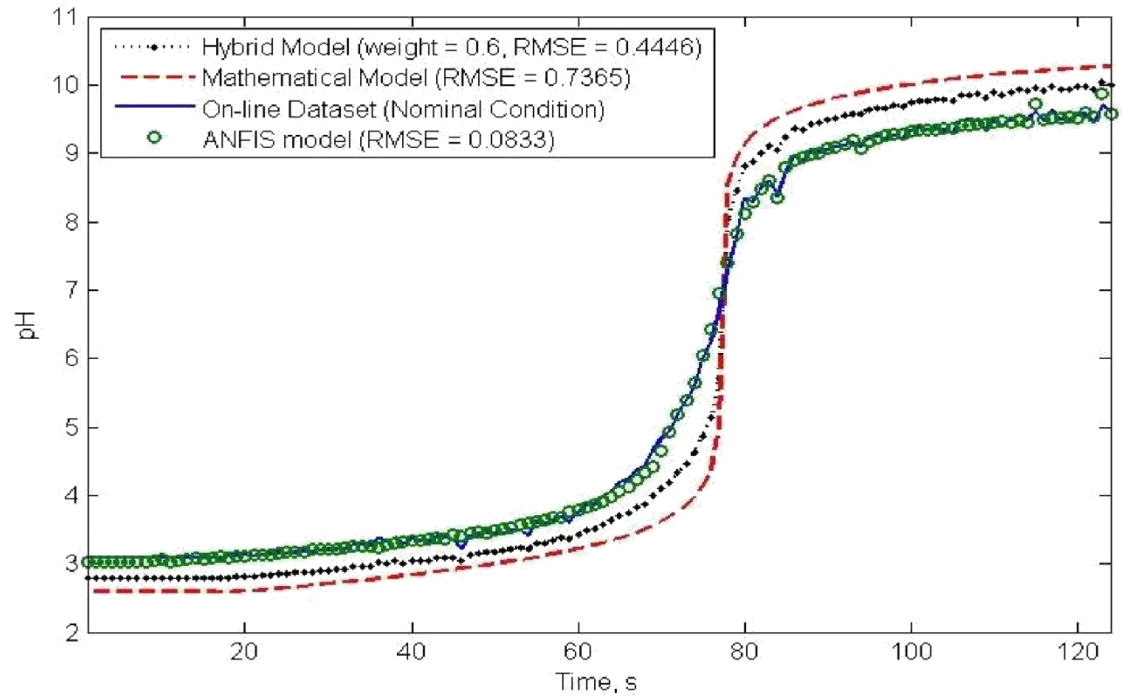


Figure 6.3: Dynamic model profiles of pH neutralization at nominal working condition

However, the hybrid model with dynamic weight is the best model, which produced a RMSE of 0.1013 as in Figure 6.4. The weight is always changing depending on magnitude of models error. The on-line data signal was channelled to mathematical model equation and neuro-fuzzy model framework. The profile was observed and at normal working condition, neuro-fuzzy model is accurate compared to mathematical model. Thus, the dynamic weight value is always less than 50%, which showed that the hybrid model was influenced by the neuro-fuzzy model.

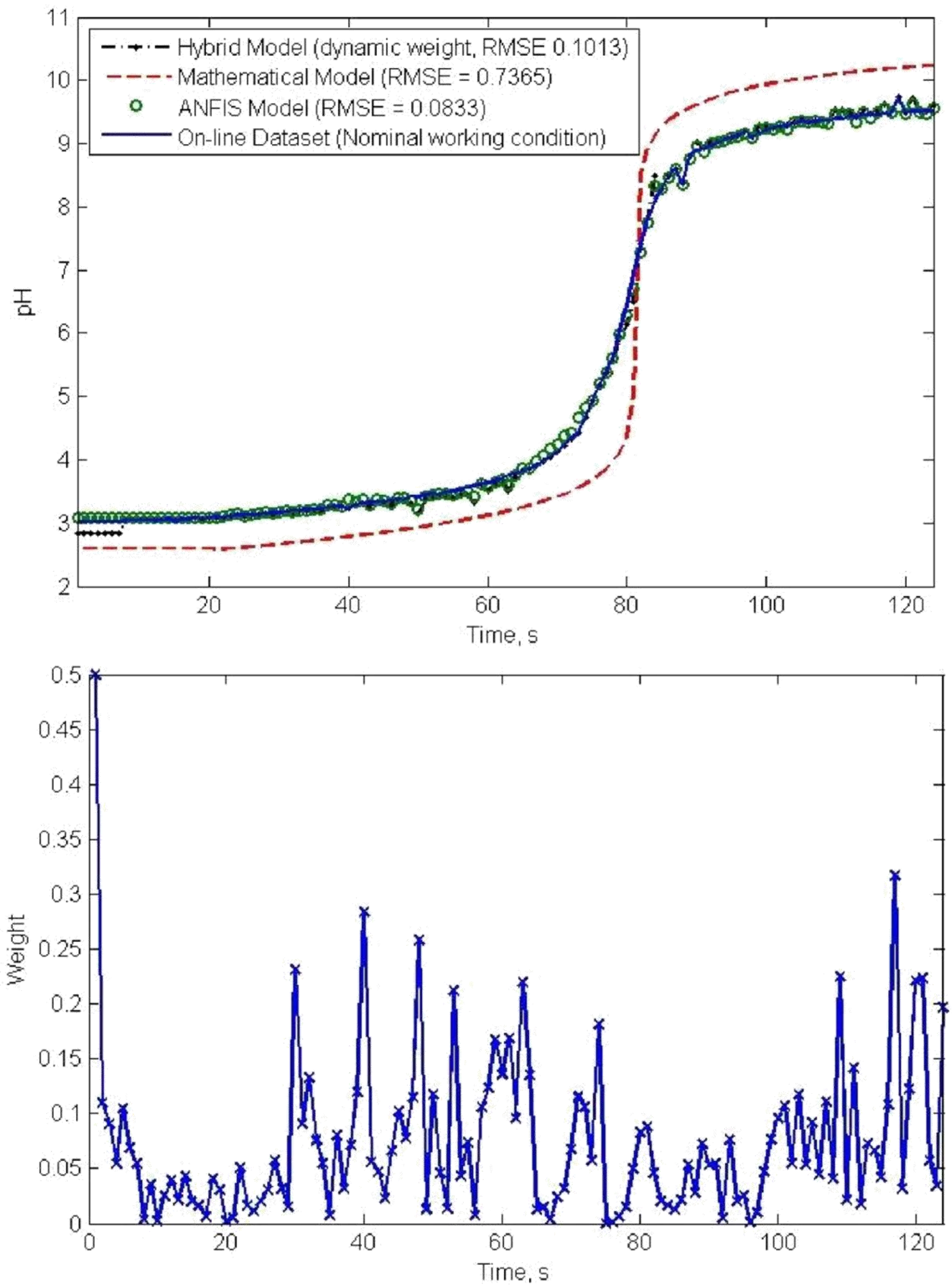


Figure 6.4: Nominal working condition profiles for Mathematical, ANFIS, and Hybrid model

6.2 Controller Tests

The controllability is the most common criteria for analysis of controller performance. In continuous time application, controllability is known as the capability for a designed controller to reach a reference point from one point to another and hold the point when disturbance occur. Thus, it is necessary to conclude that designed controller is able to drive (Set point Tracking) and maintain (Disturbance rejection) process variable in control system at desired point.

6.2.1 Set-point tracking: PID controller

The result in Figure 6.5 shows that PID controller is able to track the pH value at pH 6 and 7 but not at pH 8. Large overshoot occurred in the system before system reached steady state. Time response for pH to settle down from step change of 6 to 7 is around 150 seconds.

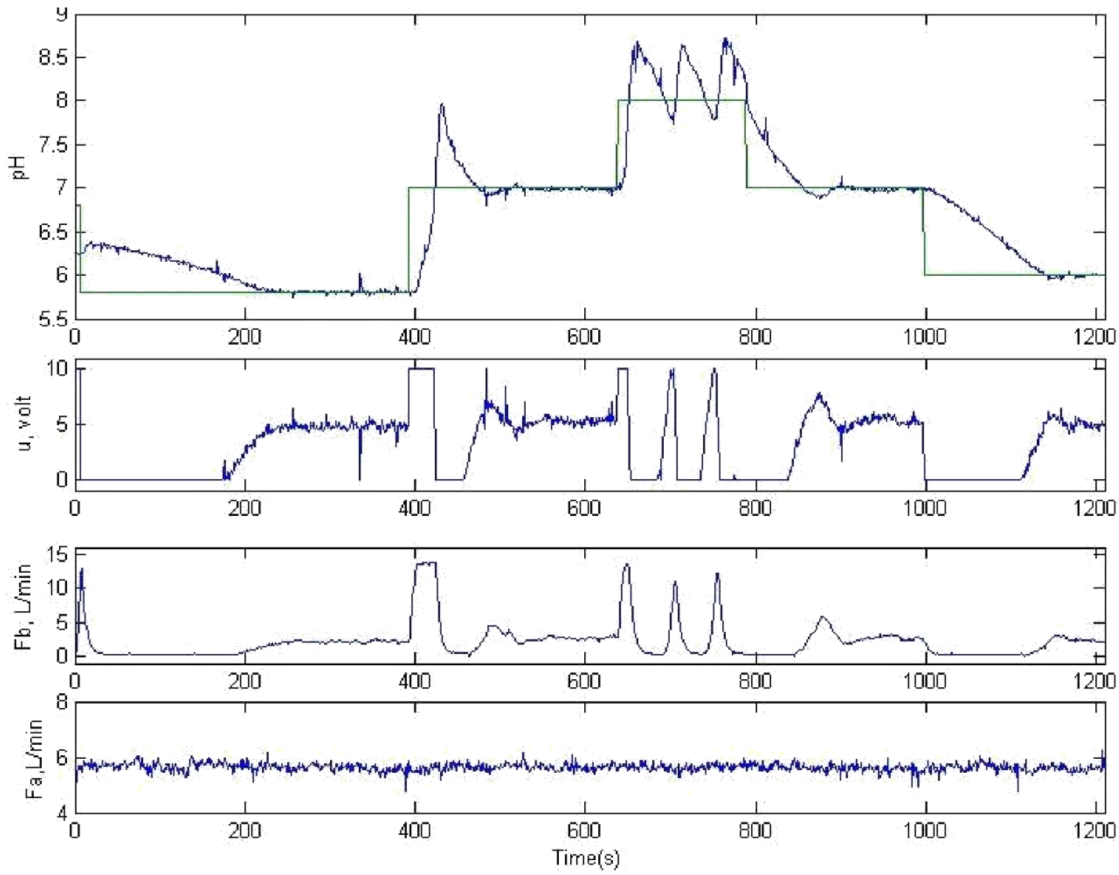


Figure 6.5: Set point tracking by using PID controller

In Figure 6.5 above, the control action value is stable at neutralization region (pH = 7) and acid region (pH = 6) but not at base region (pH = 8). At base region, controller is not stable since it varies from minimum to maximum. At this region process variable produces continuous oscillation with increment decay ratio. Acid flow rate is remaining constant with small magnitude of noise. According to Figure 6.5, the control action at steady state is 5 millivolt.

6.2.2 Set-point tracking: Fuzzy Logic controller

The controllability for set point tracking of controller is tested in pH neutralization range 6.5 to 7.5. Pilot plant is maintained at pH before applying a unit step 7.5, 6.5 and 7.0 for reference value. As shown in Figure 6.6, Fuzzy Logic controller can track the step change of pH from 7 to 7.5. The medium overshoot occurs and decay ratio is reduced until process-variable (pH) reaches steady state.

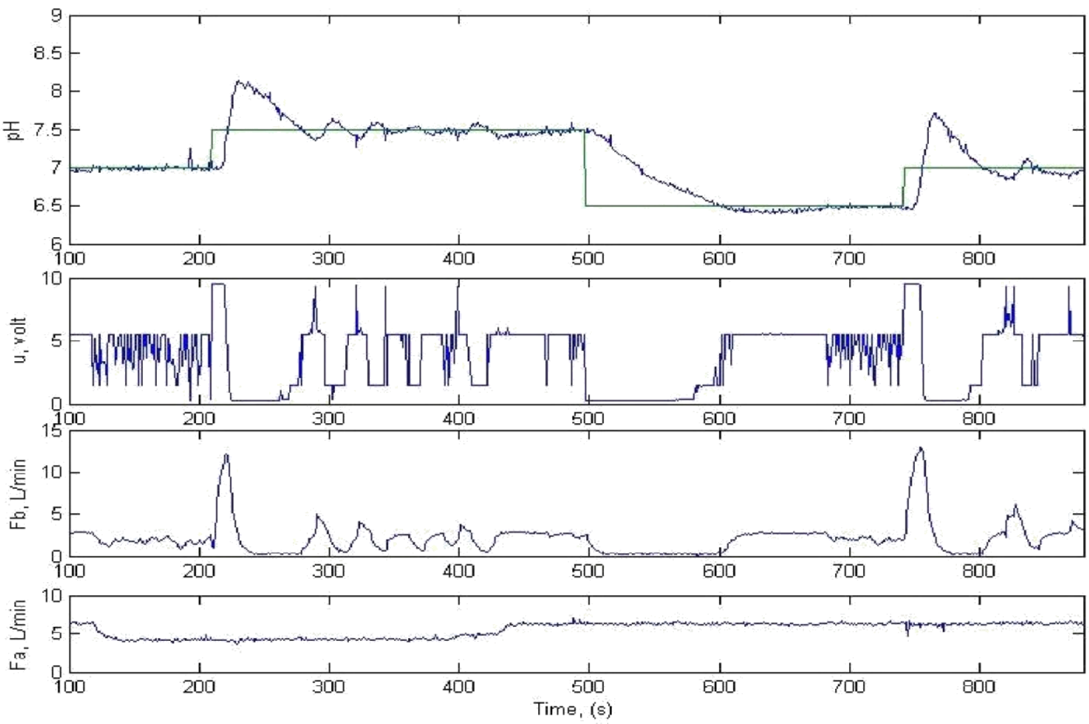


Figure 6.6: Set point tracking by using Fuzzy logic controller

The set point tracking study is continued at acid region (pH = 6.5). The result shows, at this region Fuzzy logic controller can perform well. The same performance has been recorded at neutralization region (pH = 7). It shows medium overshoot and reduced decay ratio. The time response for Fuzzy Logic controller is 150 seconds. The control action in Figure 6.6 above is populated at range 2 to 5 millivolt for steady state.

6.2.3 Set-point tracking: Hybrid Fuzzy Logic controller

In Figure 6.7, Hybrid Fuzzy Logic controller successfully in tracking the set point at several changes. The set point step is used at time 10^{th},190^{th},420^{th}, and 700^{th} seconds. From pH profile, there are no overshoots in base and neutralization regions. The response time is 90 seconds for step change from 7.2 to 8, while there is a large response time at second step change. At 420^{th} seconds, a little overshoot is observed and time response is 90 seconds.

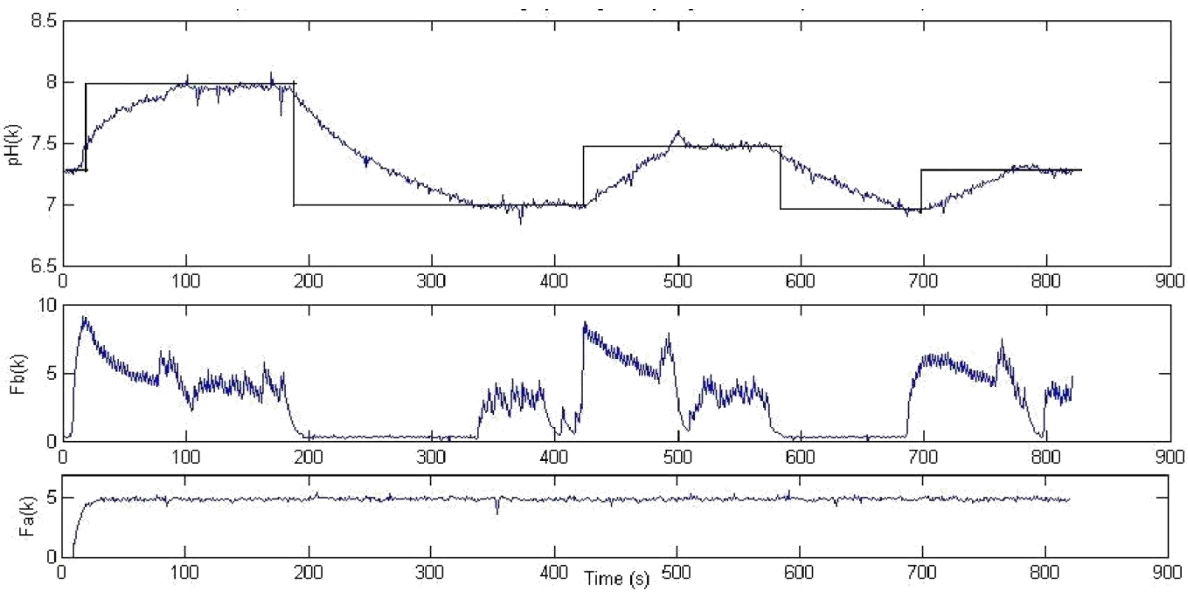


Figure 6.7: Set point tracking by using Hybrid Fuzzy Logic controller

6.2.4 Disturbance rejection: PID controller

In Figure 6.8, the disturbance occurs at time 1480 seconds following increment in step change for acid flow rate. The increment is from 5.7 to 8.3 litre/min. This disturbance produces a change in process-variable (pH). At this time pH value drops by 0.1. The PID controller gives the corrective action to compensate for the disturbance by increasing the flow rate of base from 2.8 to 4.6 litre/min.

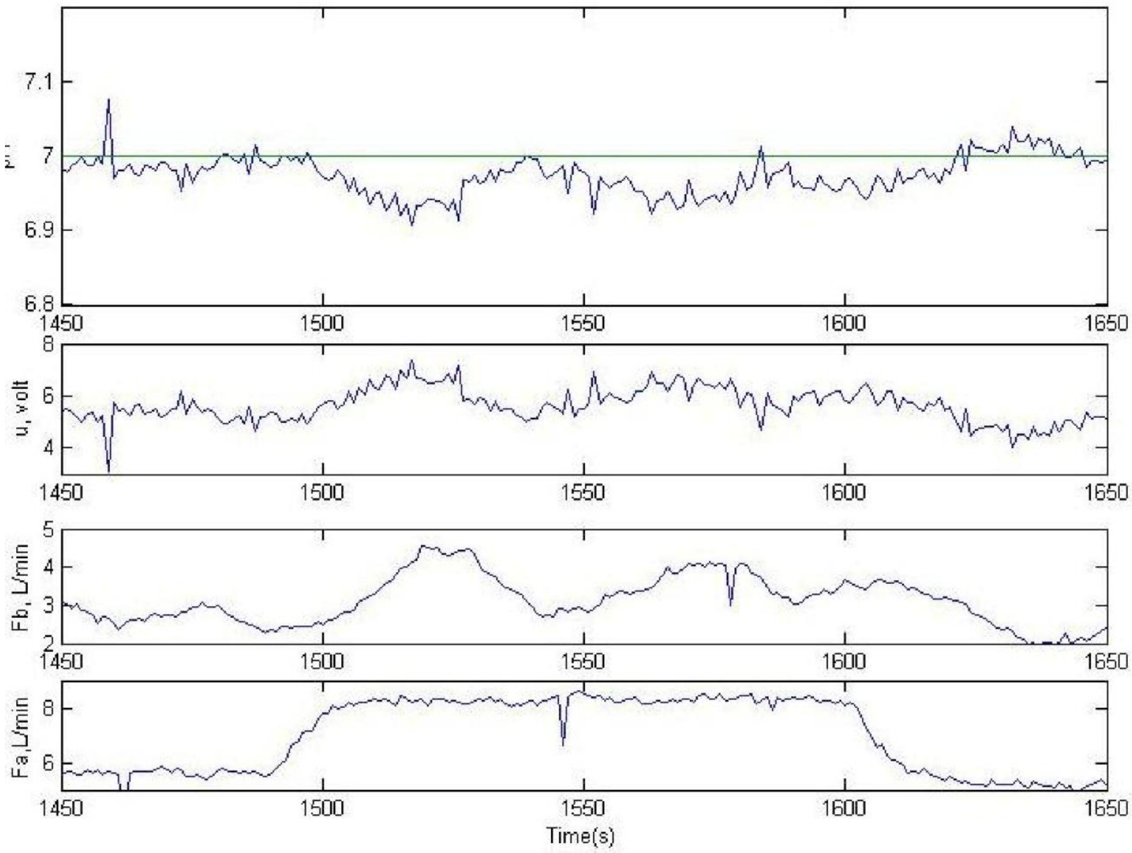


Figure 6.8: Disturbance rejection by using PID controller

The corrective action is carried out but it fail to bring the pH at 7 until the acid flow rate returned at initial condition (5.7 litre/min).

6.2.5 Disturbance rejection: Fuzzy Logic controller

In Figure 6.9, the disturbance has occurred at several time span. First, the disturbance at time 150th, 240th,300th, 360th, and 540th seconds. The disturbance changes are in range of 1.5 to 6 litre/min. The process variable is maintained by Fuzzy Logic controller, which gives immediate corrective action. There is no change in the pH profile after disturbance is introduced.

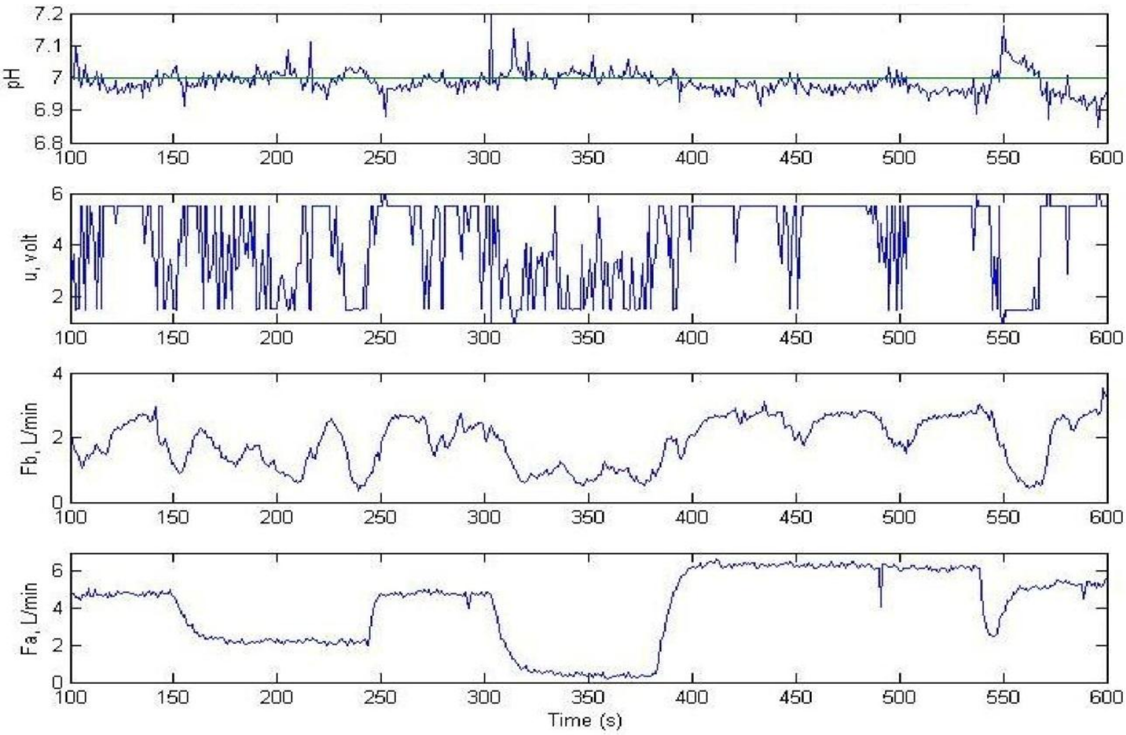


Figure 6.9: Disturbance rejection by using Fuzzy Logic controller

In Figure 6.9, Fuzzy Logic generates more frequent control action to reject the disturbance. It gives the flow rate not stable and keeps changing from time to time. The control action produce flow rates in range of 1.5 to 5.8 litre/min while the flow rate of base at 0.5 to 3.8 litre/min.

6.2.6 Disturbance rejection: Hybrid Fuzzy Logic controller

Figure 6.10 shows, disturbance occurred once at time 40th second. The large step change disturbance from 5.7 to 11 litre/min is observed. The process-variable show decrease oscillation which lead the system to steady state.

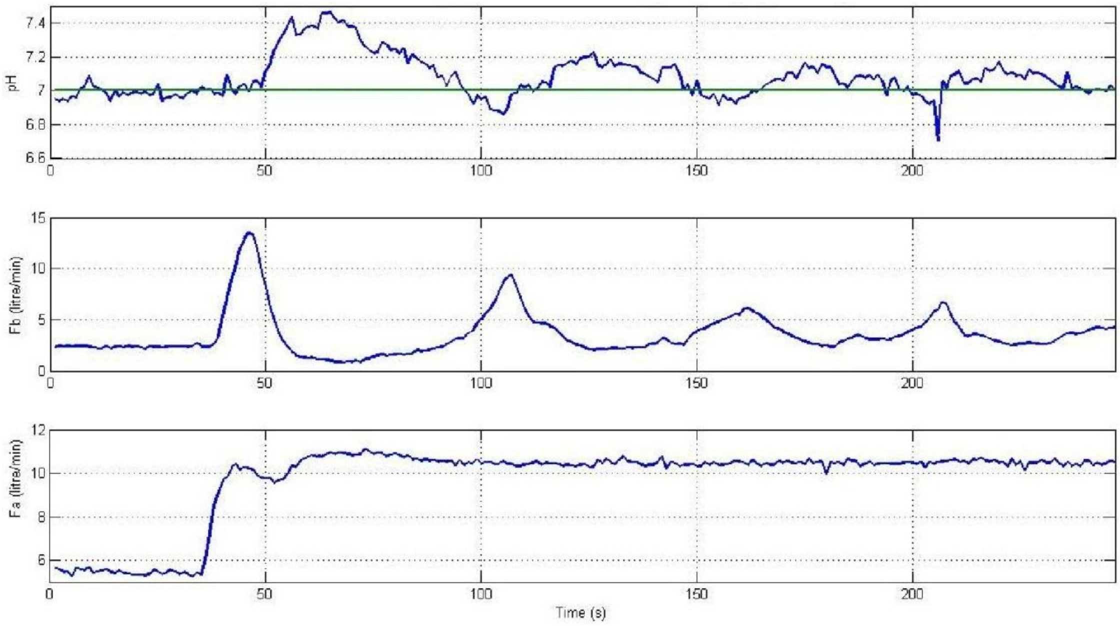


Figure 6.10: Disturbance rejection by using Hybrid Fuzzy Logic controller

In Figure 6.10, the flow rate of base is in range 4.7 litre/min. The large response time is detected for Hybrid Fuzzy Logic controller to reject the disturbance affect.

6.2.7 Set-point tracking comparison

The controllability for set point tracking of controller is tested in pH neutralization range 6.5 to 7. This range is identified as the most challenging in pH neutralization process. As shown in Figure 6.11, all controllers succeed to reach desired set point. PID controller has largest overshoot and fastest time response compared to others controller followed by Fuzzy Logic and Hybrid Fuzzy Logic controller.

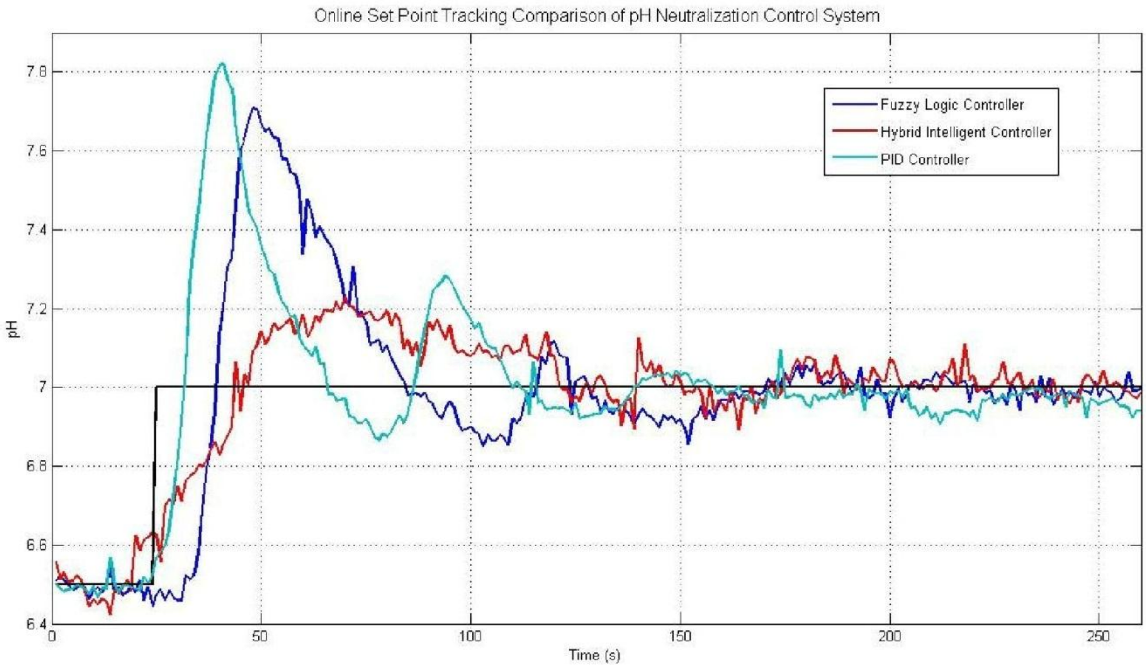


Figure 6.11: Set point tracking result of on-line pH neutralization

Integral Square Error (ISE) is used to find the goodness of the controllers above. The lower the ISE number shows that controller is better compared to other controllers. Table 6.1 shows that Hybrid Fuzzy Logic Controller has lowest ISE number which mean it this controller produces less error at achieving the set point 7.

Table 6.1: ISE comparison for set point analysis among the controllers

Controller	ISE
PID Controller	195.365
Fuzzy Logic Controller	157.652
Hybrid Fuzzy Logic Controller	35.032

6.3 Controller performances on Robustness issues

In Figure 6.12 below, the process-variable drops drastically after adding 1M HCl into the reacting tank at time 1710th seconds. The pH value drops from steady state (pH = 7) to pH 6.3. The Hybrid Fuzzy Logic controller is able to give the corrective action to compensate for the sudden change in the reactor.

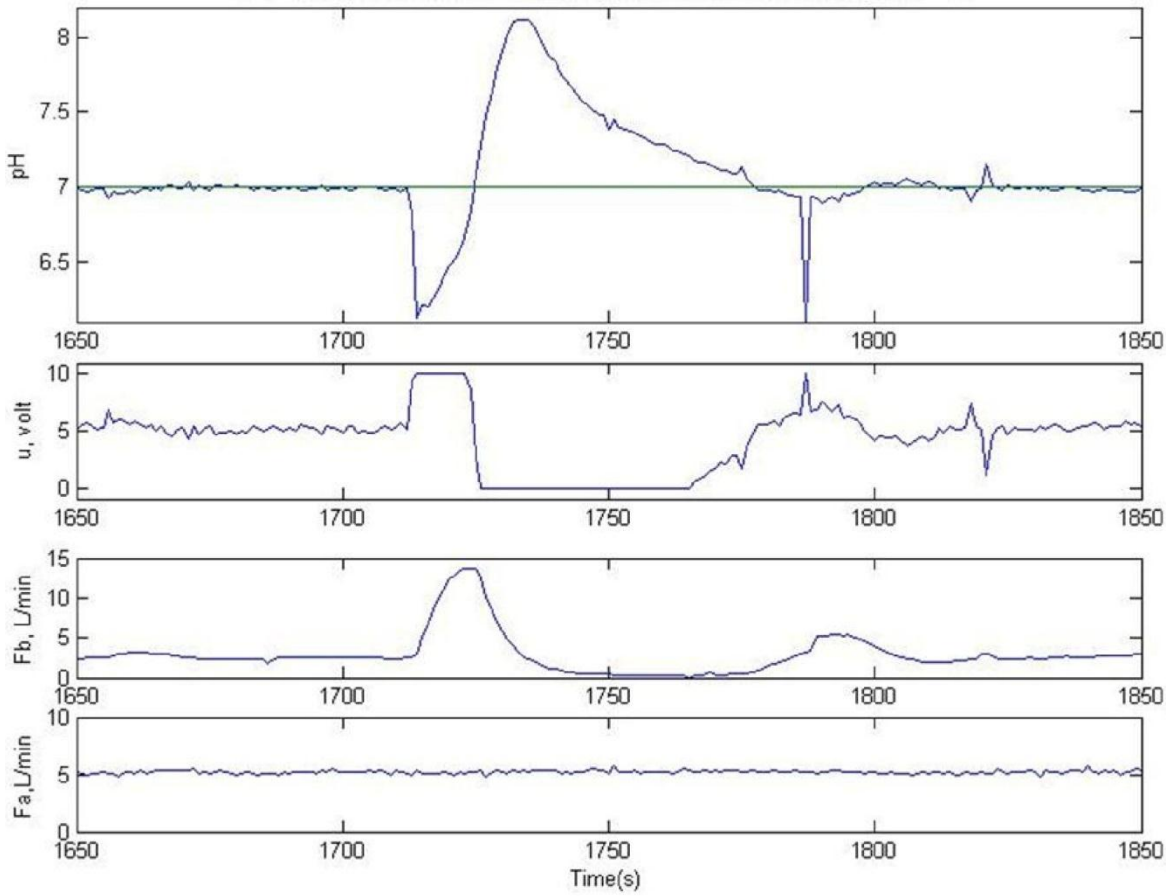


Figure 6.12: Robustness study by using Hybrid Fuzzy Logic controller
(Altered effect in mixing reactor by adding 5ml HCL 1M)

In Figure 6.12, shows the increments of control action due to a sudden drop of reactor concentration. It goes back to 5 millivolt which a previous steady state control action. In Figure 6.13, the problem happens when the controlled stream became clogged. At the first attempt, the clog start at 10% and the Hybrid Fuzzy Logic controller give maximum control action to control valve but it fails to bring up the process-variable. It is because the amount of NaOH entering the mixing reactor is not enough to compensate for the HCl composition in the tank. The second attempt is to open at 50% of the NaOH pipeline. At this time, the Hybrid Fuzzy Logic controller succeeds to bring the pH value up to the desired set point with little overshoots. However, there is a delay detected at initial corrective action at time 2465th to 2472th seconds. It is due to the large amount of HCL composition that populated the mixing tank due to the previous attempt.

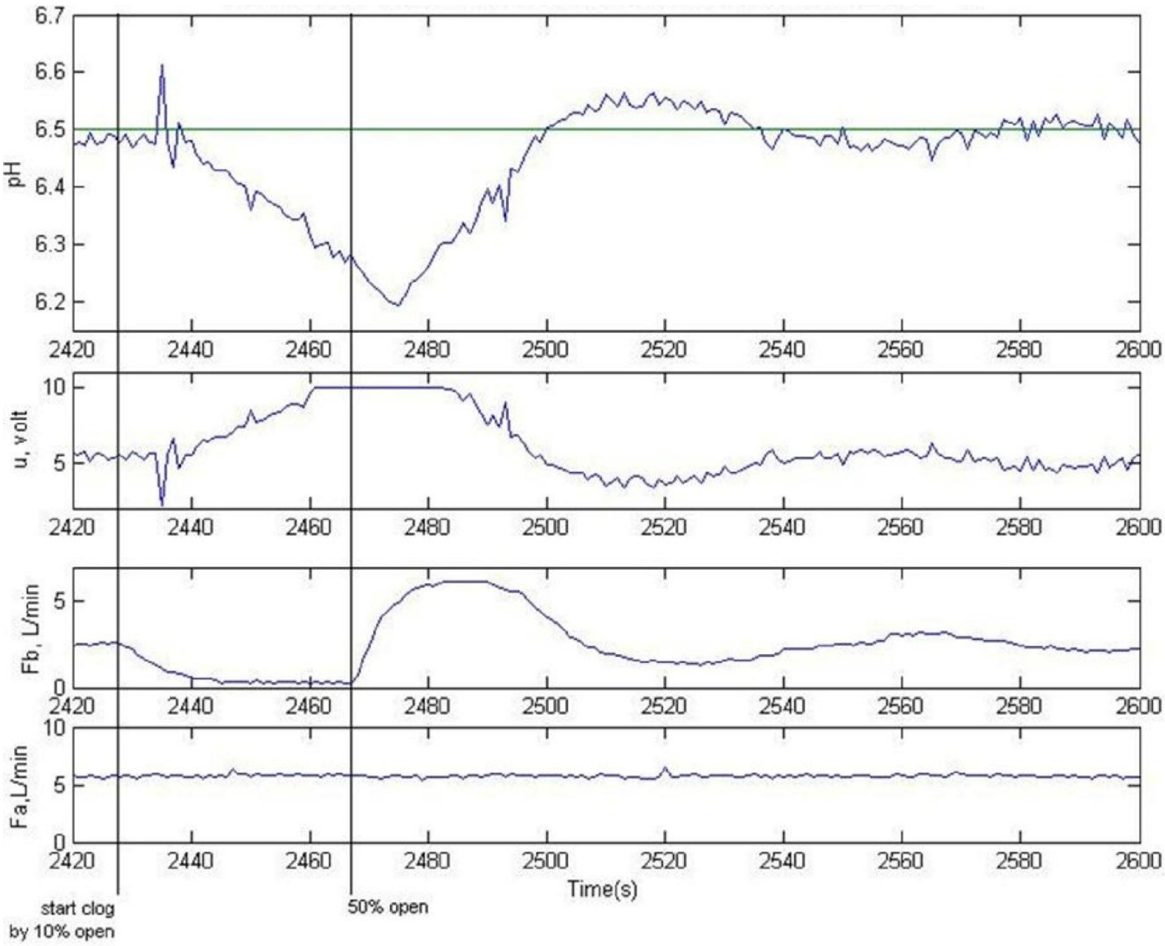


Figure 6.13: Robustness study by using Hybrid Fuzzy Logic controller (Equipment failure at controlled stream)

Chapter 7 : Conclusion

7.1 The research novelty

The research novelties that this study proposed are:

(1) Hybrid technique of physical and empirical model

First, the proposed model of pH neutralization has been produced from first principle and Adaptive Neural Fuzzy Inference System (ANFIS). The mechanic behind this hybrid is in “Research Methodology” chapter. In general, this hybrid is a combination of two output-models, which predicts the pH value. The novelty is mainly to manage the individual output-model. The hybrid model has been validated with on-line pH neutralization experiment and has shown a good fit (at nominal or altered conditions).

(2) The adjustment at output membership-function for Sugenno’s fuzzy inference by introducing inverse hybrid model in Fuzzy Logic controller.

Second, this study proposed the improvement on robustness issues (in altered plant condition) in Fuzzy Logic controller. The study improved Sugenno’s fuzzy inference arrangement, which changed the output membership-function. The adjustment has been made by substituting the normal output (constant or linear-function) with inverse model prediction (model is from previous finding above). The details of the adjustment are described in the “Research Methodology” chapter. By performing this adjustment, the Fuzzy Logic controller is more robust when carrying out the on-line control for pH neutralization plant. The adjusted Fuzzy Logic controller performed well compared with conventional and Fuzzy Logic controller (with or without robustness variations).

7.2 Achievement of research objectives

1. The hybrid model has been obtained in this study.

The hybrid model was applied to full-scale reaction of strong acid and strong base in a pH neutralization plant. Parallel type was the selected hybrid model structure. Online performance analysis was conducted and compared. A mathematical model pH system was compared with an ANFIS model pH system. A hybrid model was investigated through several hybrid weight values α. ANFIS model alone is an insufficient representation of pH dynamics if plant parameters is altered. Mathematical model alone cannot best predict real pH value. The hybrid model, which combines the advantages of the two models and meets the study objectives, is proposed. With dynamic weight algorithm, it gives the best fit and can be used effectively in online/offline studies of dynamic behaviour of plant pH neutralization system.

2. The Fuzzy Logic controller has been improved by inverse hybrid model.

A novel Hybrid Fuzzy Logic controller is proposed as the best advanced controller for a nonlinear pH neutralization process control system. It is a blending between empirical method and mathematical algorithm and this mechanism improved Sugeno type Fuzzy Logic for robustness problem. The results have shown that it is more superior to the other controllers (PID and Fuzzy Logic controller) in handling set point tracking and disturbance rejection. The proposed controller has promising potential for other nonlinear control system applications like polymerization, fermentation and many more.

7.3 Future work

The study can be extended for

1. Model and controller stability analysis
2. Apply proposed hybrid model and fuzzy logic controller to other nonlinear processes
3. Improve the pilot plant design and instrument so that more advanced controllers could be investigated
4. Implement the control system for real applications, for example, use real wastewater instead of using standard acid and base.
5. Software interface since the control system is depended solely on MATLAB/Simulink.

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Appendix A: Programming Code

File Name: ANFISMethod.m

```
%% ANFIS method for pH model identification
   %% Load      traning
      Dataset       run
      'PrepTrnDataset'
trn_data    =    trndata(:,:);    %from    load
'PrepChkDataSet.m' chk_data = trn_data;
%% Select proper inputs to the model
run 'InputSelection'
%% Generate training ANFIS
Matrix %to prediction pH
ss = 0.01;
ss_dec_rate =
0.5;
ss_inc_rate =
1.5;
%Final dataset for training data
trn_data = trndata(:, [input_index,
size(trndata,2)]); chk_data = trndata(:,
[input_index, size(trndata,2)]);
% generate FIS matrix
in_fismat =
genfis1(trn_data);
[trn_out_fismat trn_error step_size chk_out_fismat chk_error] =
...
    anfis(trn_data, in_fismat, [1 nan ss ss_dec_rate
    ss_inc_rate],
...
    nan, chk_data, 1);
%% Show result
outTrn_pH = evalfis(trndata(:,input_index),
trn_out_fismat); index = 1:length(outTrn_pH);
plot(index, trndata(:, size(trndata,2)), '-', index,
outTrn_pH, '.');
rmse  =  norm(outTrn_pH(index)-
trndata(index,size(trndata,2)))/...
       sqrt(length(index));
title(['Training Data (Solid Line) & ANFIS Prediction (Dots)
with RMSE = '...

        num2str(rmse)]);
xlabel('Time Index');
```

```
ylabel('');
```

File Name: PrepTrnDataSet.m

```
   %% ANFIS   method   for   pH   model
      identification      %PART      I:
      TrnDataset
   %%
load TrnDataSet
%% Check Time delay
trndata_n = length(TrnDataSet);
subplot(3,1,1);plot(TrnDataSet(1:trndata_n
,1))
subplot(3,1,2);plot(TrnDataSet(1:trndata_n
,2))
subplot(3,1,3);plot(TrnDataSet(1:trndata_n
,3))

%%
%1 output : pH
pH =
TrnDataSet(:,3);
output = pH;
%10 inputs : Fa(k-a),Fa(k-b),Fa(k-c),Fa(k-d),Fa(k-
e), & % Fb(k-m),Fa(k-n),Fa(k-p),Fa(k-q),Fa(k-r)

input1  =  [0;  ...
          TrnDataSet(1:trndata_n-1,1)];
input2  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          TrnDataSet(1:trndata_n-40,1)];
input3  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          TrnDataSet(1:trndata_n-50,1)];
input4  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          TrnDataSet(1:trndata_n-60,1)];
input5  =[0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
         0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
         0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
         0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
         0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
         0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
         0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
         TrnDataSet(1:trndata_n-70,1)];
input6  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
          0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
```

```
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...

        TrnDataSet(1:trndata_n-60,2)];
input7  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        TrnDataSet(1:trndata_n-70,2)];
input8  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  TrnDataSet(1:trndata_n-73,2)];
input9  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;  ...
        0;  0;  TrnDataSet(1:trndata_n-82,2)];
input10  =  [0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;  0;  0;  0;  0;  0;  0;  0;  0;  0;...
        0;0;TrnDataSet(1:trndata_n-102,2)];

input  =  [input1  input2  input3  input4  input5...
        input6  input7  input8  input9  input10];

trndata = [input

output]; trndata(1:6,

:) = [];

input_name1 = 'Fa(k-1)';
input_name2 = 'Fa(k-
40)'; input_name3 =
'Fa(k-50)'; input_name4
= 'Fa(k-60)';
input_name5 = 'Fa(k-
70)'; input_name6 =
'Fb(k-72)'; input_name7
= 'Fb(k-73)';
```

```
input_name8 = 'Fb(k-
74)'; input_name9 =
'Fb(k-82)'; input_name10
= 'Fb(k-102)';
```

File Name: InputSelection.m

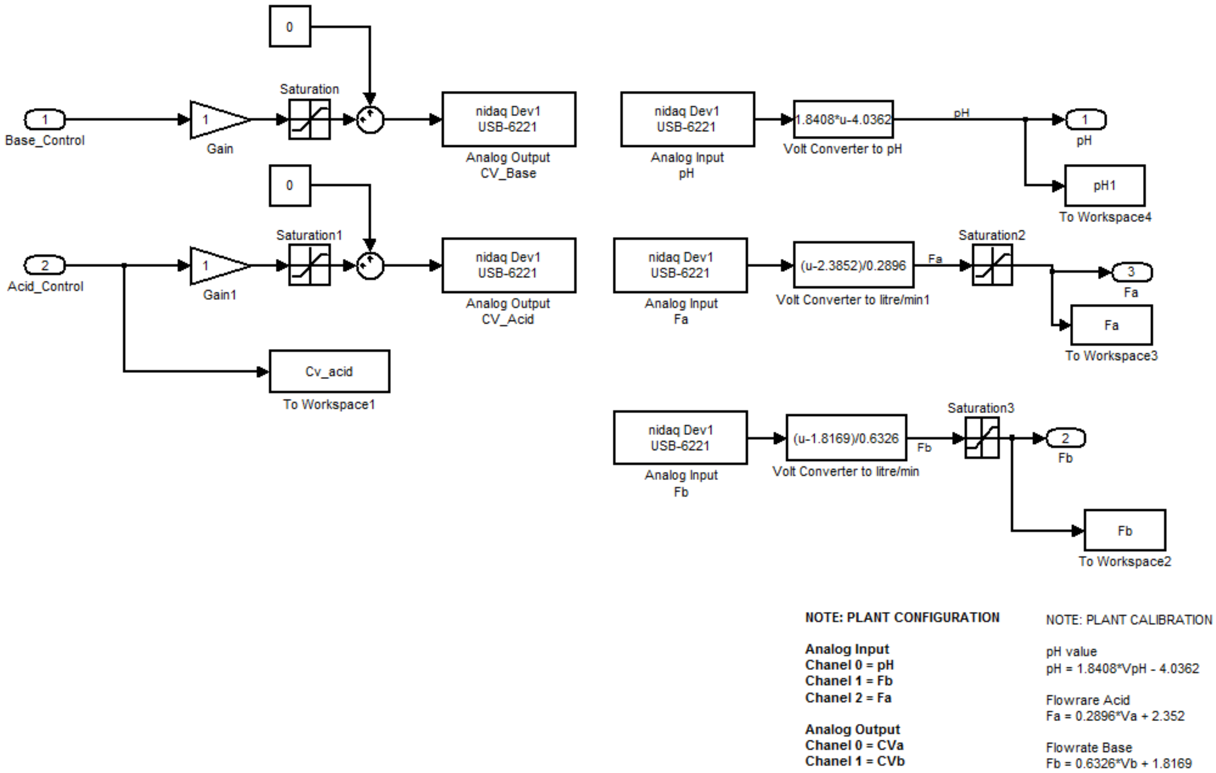
```
%% To use ANFIS we need to select the input.
   % That is, to determine which variables should be the
     input to the model.
% We used 10 inputs candidate; and the output is pH(k)
% Input selection is selected by sequential forward
  search
% to optimize the Root Mean Square Error (RMSE).

%NOTE: we can use other method like Exhaustive search, GA, PSO,

and % other optimization tools

input_name = str2mat(input_name1,input_name2,input_name3,...

input_name4,input_name5,input_name6,input_name7,...
                      input_name8,input_name9,input_name10);

[input_index, elapsed_time] = seqsrch(3, trn_data,
chk_data, input_name);
fprintf('\nElapsed time = %f\n',
elapsed_time); winH1 = gcf;

% Group the selected input
 group1 = [1 2 3 4]; % y(k-a), y(k-b), y(k-c), y(k-d)
group2 = [1 2 3 4]; % y(k-m), y(k-n), y(k-p), y(k-q)

group3 = [5 6 7 8 9 10]; % u(k-1) through y(k-6)

anfis_n = 6*length(group3);
index = zeros(anfis_n, 3);
trn_error = zeros(anfis_n,
1); chk_error =
zeros(anfis_n, 1);

   % ======= Training
     options mf_n =
     3;
mf_type =
'gbellmf';%
epoch_n = 1;
ss = 0.1;
ss_dec_rate =
0.5;
ss_inc_rate =
1.5;
   % ====== Train ANFIS with different input variables
     fprintf('\nTrain %d ANFIS models, each with 3 inputs
     selected from 10 candidates...\n\n',...
    anfis
_n);
model =
1;
```

```
for  i=1:length(group1),
    for
        j=i+1:length(group2
        ), for
        k=1:length(group3),
            in1  =  deblank(input_name(group1(i),
            :));              in2              =
            deblank(input_name(group2(j),     :));
            in3  =  deblank(input_name(group3(k),
            :));

            index(model, :) = [group1(i) group2(j) group3(k)];
            trn_data = trndata(:, [group1(i) group2(j) group3(k)
            ...
                        size(trndata,2)]);
            chk_data  =  trndata(:,  [group1(i)  group2(j)  group3(k)
            ...
                        size(trndata,2)]);
            in_fismat = genfis1(trn_data, mf_n, mf_type);
            [trn_out_fismat t_err step_size chk_out_fismat c_err]
            =
...
                anfis(trn_data,  in_fismat,  ...
                [epoch_n  nan  ss  ss_dec_rate  ss_inc_rate],
                ...
                [0 0 0 0], chk_data,
            1); trn_error(model) =
            min(t_err);
            chk_error(model) =
            min(c_err);
            fprintf('ANFIS  model  =  %d:  %s  %s  %s',  model,  in1,
            in2,
in3);
            fprintf(' --> trn=%.4f,',
            trn_error(model)); fprintf(' chk=%.4f',
            chk_error(model)); fprintf('\n');
            model  =  model+1;
        end
    end
end

   %  ======   Reordering   according   to
      training    error    [a    b]    =
      sort(trn_error);
b = flipud(b); % List according to decreasing trn error
trn_error = trn_error(b);
chk_error           =
chk_error(b);  index  =
index(b, :);
% ======  Display  training  and  checking  errors
x =
(1:anfis_n)';
subplot(2,1,1
);
plot(x,  trn_error,  '-',  x,  chk_error,  '-',  ...
    x, trn_error, 'o', x, chk_error,
```

```
'*'); tmp = x(:, ones(1, 3))';
X  =  tmp(:);
tmp = [zeros(anfis_n, 1) max(trn_error, chk_error)
nan*ones(anfis_n, 1)]';
Y = tmp(:);
hold on;
plot(X, Y,
'g'); hold
off;

axis([1 anfis_n -inf
inf]); set(gca,
'xticklabel', []);
% ====== Add text of input
variables for k = 1:anfis_n,
    text(x(k),  0,  ...
        [input_name(index(k,1),  :)  '  '  ...
            input_name(index(k,2),  :)  '  '  ...
            input_name(index(k,3),  :)]);
end
h  =  findobj(gcf,  'type',  'text');
set(h,  'rot',  90,  'fontsize',  11,  'hori',  'right');


drawnow

% ====== Generate
input_index [a b] =
min(trn_error);
input_index = index(b,:);
title('Training (Circles) and Checking (Asterisks)
Errors'); ylabel('RMSE');
```

Appendix B: MATLAB/Simulink

1. Pilot Plant Data Acquisition Block Diagram



2. Collecting Online Dataset

```
sizeFb = size(Fb.signals.values(:,:,:),3);
for i = 1:sizeFb
time(i) = i;
CVa(i) = Cv_acid.signals.values(i);
CVb(i) = Cv_base.signals.values(i);
FaData(i) = Fa.signals.values(:,:,i);
FbData(i) = Fb.signals.values(:,:,i);
pHData(i) = pH1.signals.values(:,:,i);
end

Dataset = horzcat(FaData',FbData',pHData');
```