# APPLICATIONS OF FIS, ANN AND ANFIS TO INDUSTRIAL CONTROL

**BY**

**MR.PRASERT AENGCHUAN**

**A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY PROGRAM IN ENGINEERING**

**DEPARTMENT OF INDUSTRIAL ENGINEERING**
**FACULTY OF ENGINEERING**
**THAMMASAT UNIVERSITY**
**ACADEMIC YEAR 2015**

# APPLICATIONS OF FIS, ANN AND ANFIS TO INDUSTRIAL CONTROL

**BY**

**MR.PRASERT AENGCHUAN**

**A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY PROGRAM IN ENGINEERING**

**DEPARTMENT OF INDUSTRIAL ENGINEERING**
**FACULTY OF ENGINEERING**
**THAMMASAT UNIVERSITY**
**ACADEMIC YEAR 2015**

THAMMASAT UNIVERSITY

FACULTY OF ENGINEERING

DISSERTATION

BY

MR. PRASERT AENGCHUAN

ENTITLED

APPLICATIONS OF FIS, ANN AND ANFIS TO INDUSTRIAL CONTROL

was approved as partial fulfillment of the requirements for the degree of Doctor of Philosophy Program in Engineering

on November 18, 2015 by

Chairman ______________________

(Asst. Prof. Dr. Apiwat Muttamara)

Member and Advisor ______________________

(Assoc. Prof. Dr. Busaba Phruksaphanrat)

Member ______________________

(Assoc. Prof. Dr. Pongchanun Luangpaiboon)

Member ______________________

(Assoc. Prof. Dr. Sanya Mitaim)

Member ______________________

(Dr. Wuttinan Nunkaew)

Dean ______________________

(Assoc. Prof. Dr. Prapat Wangskarn)

| | |
|---|---|
| หัวข้อดุษฎีนิพนธ์ | การประยุกต์ใช้ FIS, ANN และ ANFIS กับการควบคุมในอุตสาหกรรม |
| ชื่อผู้เขียน | นายประเสริฐ เอ่งฉ้วน |
| ชื่อปริญญา | ปรัชญาดุษฎีบัณฑิต (วิศวกรรมศาสตร์) |
| สาขาวิชา/คณะ/มหาวิทยาลัย | วิศวกรรมอุตสาหการ<br>วิศวกรรมศาสตร์<br>มหาวิทยาลัยธรรมศาสตร์ |
| อาจารย์ที่ปรึกษาดุษฎีนิพนธ์ | รองศาสตราจารย์ ดร. บุษบา พฤกษาพันธุ์รัตน์ |
| ปีการศึกษา | 2558 |

## บทคัดย่อ

ดุษฎีนิพนธ์นี้นำเสนอการเปรียบเทียบระหว่าง ฟัซซี่ลอจิก (FIS), โครงข่ายประสาทเทียม (ANN) และ Adaptive Neuro-Fuzzy Inference System (ANFIS) โดยนำมาประยุกต์ใช้กับปัญหาการควบคุมกระบวนการผลิตและการควบคุมพัสดุคงคลัง ในการควบคุมในภาคอุตสาหกรรมแบบดั้งเดิมของการควบคุมกระบวนการผลิตและการควบคุมพัสดุคงคลัง ส่วนใหญ่แล้วจะเกี่ยวข้องกับข้อมูลหรือตัวแปรป้อนเข้าที่ทราบค่าแน่นอน ซึ่งไม่เหมาะสมในภาคปฏิบัติและไม่สอดคล้องกับความเป็นจริง วิธีการที่มีอยู่ก็ไม่สามารถจัดการกับข้อมูลหรือตัวแปรที่มีความไม่แน่นอนได้ทั้งหมด ในปัจจุบันมีตัวแบบที่มีประสิทธิภาพในการจัดการปัญหาดังกล่าวและมีการนำไปประยุกต์ใช้กันอย่างแพร่หลายเพื่อจัดการกับความไม่แน่นอนดังกล่าว คือ FIS, ANN และ ANFIS ดังนั้นวิธีการดังกล่าวจึงถูกนำเสนอในดุษฎีนิพนธ์นี้ ทั้งการควบคุมกระบวนการผลิตและการควบคุมพัสดุคงคลังกับโรงงานกรณีศึกษาของแต่ละการประยุกต์ใช้งาน แต่อย่างไรก็ตามตัวแบบที่เหมาะสมที่สุดสำหรับปัญหาแต่ละปัญหายังมิได้มีการศึกษาเปรียบเทียบไว้

สำหรับการประยุกต์ใช้กับการควบคุมกระบวนการผลิตถูกนำไปพิจารณากับกรณีศึกษาโรงงานผลิตยิบซั่มโดยทำการเปรียบเทียบทั้ง 3 ตัวแบบ สำหรับตัวแบบ FIS ข้อมูลจากกระบวนการผลิตถูกนำมาแปลงเป็นตัวแปรแบบฟัซซี่ แล้วสร้างกฎแบบฟัซซี่เพื่อนำไปหาค่าของตัวแปรควบคุมแบบฟัซซี่ แล้วแปลงเป็นตัวแปรควบคุมเพื่อนำไปใช้ในการควบคุมกระบวนการผลิตต่อไป สำหรับตัวแบบ ANN ข้อมูลจากกระบวนการผลิตถูกนำมาสอนและทดสอบจนกว่าจะได้ค่าผิดพลาดต่ำที่สุด แล้วนำค่าตัวแปรที่ได้ไปใช้ในการควบคุมกระบวนการผลิตต่อไป ในทำนองเดียวกันสำหรับตัวแบบ ANFIS ก็ใช้ข้อมูลจากกระบวนการผลิตมาสอนและทดสอบจนกว่าจะได้ค่าผิดพลาดต่ำที่สุด แล้วนำค่าตัวแปรที่ได้ไปใช้ในการควบคุมกระบวนการผลิตต่อไป โดยมีการศึกษาฟังก์ชันสมาชิก 3 แบบคือ Trap (รูปแบบ trapeziodal ผสมกับ triangular), Gaussian และ Bell shape ทุกตัวแบบที่ศึกษาได้ถูกนำมาเปรียบเทียบค่าที่ได้กับค่าจริงจากกระบวนการผลิต ผลที่ได้พบว่า ตัวแบบ ANFIS_Bell แสดงผลด้านประสิทธิภาพได้ดีที่สุดและสามารถช่วยลดของเสียในกระบวนการผลิตยิบซั่มได้ 5.2% เมื่อนำไปใช้งานจริงในกระบวนการผลิตของโรงงานกรณีศึกษา

สำหรับการประยุกต์ใช้กับการควบคุมพัสดุคงคลังถูกนำไปพิจารณากับกรณีศึกษาโรงงานผลิตเฟอร์นิเจอร์ ตัวแปรป้อนเข้าแบบฟัซซี่คือ ความต้องการสินค้าและปริมาณของวัตถุดิบที่รับเข้ามาซึ่งมีความไม่แน่นอน สำหรับตัวแบบ FIS กฎของฟัซซี่จะถูกสร้างขึ้นเพื่อนำไปหาค่าปริมาณการสั่งซื้อแบบฟัซซี่แต่ละค่าอย่างต่อเนื่อง ปริมาณการสั่งซื้อที่ได้จะถูกปรับปรุงจากค่าตามตัวแบบ FIS กับอัลกอลิทึมสำหรับประเมินปริมาณการสั่งซื้อ (order quantity evaluation algorithm) ผลลัพธ์ที่ได้จากตัวแบบ FIS จะถูกใช้เป็นข้อมูลสำหรับตัวแบบ FIS+ANN และตัวแบบ FIS+ANFIS สำหรับตัวแบบ FIS+ANFIS มีการศึกษาฟังก์ชันสมาชิกเป็น 3 แบบคือ Trap, Gaussian และ Bell shape ต้นทุนของพัสดุคงคลังถูกนำมาใช้ในการเปรียบเทียบกับตัวแบบการสั่งซื้อแบบ Stochastic EOQ ผลที่ได้พบว่าตัวแบบ FIS+ANFIS_Gauss แสดงผลของประสิทธิภาพได้ดีที่สุดทางด้านของ

ต้นทุนของพัสดุคงคลังรวมซึ่งสามารถช่วยลดต้นทุนดังกล่าวได้มากกว่า 75% เมื่อเทียบกับตัวแบบการสั่งซื้อแบบ Stochastic EOQ

จากการเปรียบเทียบในการศึกษานี้จะพบว่า สำหรับข้อมูลแบบต่อเนื่อง เช่น การควบคุมกระบวนการผลิต ตัวแบบ ANFIS เหมาะสำหรับการนำไปประยุกต์ใช้งาน เพราะให้ความแม่นยำในการพยากรณ์และให้ค่าประสิทธิภาพในการใช้งานได้ดีที่สุด อีกทั้งยังช่วยลดของเสียในกระบวนการผลิต สำหรับข้อมูลแบบไม่ต่อเนื่อง เช่น การควบคุมพัสดุคงคลัง ตัวแบบ FIS+ANFIS เหมาะสำหรับนำไปประยุกต์ใช้งานเพราะให้ค่าความแม่นยำในการพยากรณ์และให้ค่าประสิทธิภาพในการใช้งานได้ดีที่สุด นอกจากนี้ตัวแบบดังกล่าวยังช่วยลดต้นทุนของพัสดุคงคลังได้เป็นอย่างดี

**คำสำคัญ:** ฟัซซี่ลอจิก, โครงข่ายประสาทเทียม (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), การควบคุมกระบวนการผลิต, การควบคุมพัสดุคงคลัง

| | |
|---|---|
| Dissertation Title | APPLICATIONS OF FIS, ANN AND ANFIS TO INDUSTRIAL CONTROL |
| Author | Mr. Prasert Aengchuan |
| Degree | Doctor of Philosophy (Engineering) |
| Major Field/Faculty/University | Industrial Engineering<br>Engineering<br>Thammasat University |
| Dissertation Advisor | Assoc. Prof. Dr. Busaba Phruksaphanrat |
| Academic Years | 2015 |

# ABSTRACT

This dissertation presented the comparison of fuzzy logic (FIS), artificial neural networks (ANN) and adaptive neuro-fuzzy inference system by applying with the problems of process control and inventory control. Conventional industrial control such as process control and inventory control mostly concern to known or deterministic input parameters which is not practical and not realistic for many industries. Existing approaches cannot entirely deal with uncertain input parameters. Recently, the effective models to deal with such kind of problems which use in numerous applications under uncertainty are fuzzy logic approach, artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) approach. So, these approaches were proposed in this dissertation for both process control and inventory control with a case study factory of each application. However, the most suitable model for each problem has not been comparatively studied.

The process control application has determined with a case study of gypsum process to compare all three models. For FIS model, inputs data from process were converted to be fuzzy variables. The generated fuzzy rules were utilized to obtain the fuzzy process control parameters. Then these parameters were converted to the process control parameters for using in process control. For ANN model, data from process control were utilized to train and test with the model until getting the lowest error. Then these control parameters were applied to control in the process. Similarly to ANFIS model, data from process control were utilized to train and test

with the model until getting the lowest error. Then these control parameters were applied to control in the process. ANFIS model was studied with 3 membership functions; trapezoidal and triangular (Trap), Gaussian and bell shape. All approaches were compared with the existing process parameters. The results indicated that the proposed ANFIS_Bell model obtained with the best performance. Moreover, the proposed ANFIS_Bell model can reduce production defects approximately 5.2% when implemented with a case study factory.

For inventory control application, the fuzzy input parameters; demand and supply which are uncertain were applied for the inventory system. For FIS model, the developed fuzzy rules were utilized to find out the fuzzy order quantity continuously. The order quantity was adjusted according to the FIS model with the order quantity evaluation algorithm for the inventory model. The output of FIS model was also applied as data for FIS+ANN and FIS+ANFIS models. The FIS+ANFIS model was studied with 3 membership functions; trapezoidal and triangular (Trap), Gaussian and bell shape. Inventory costs of the proposed models were compared with the stochastic economic order quantity (EOQ). The results represented that the FIS+ANFIS_Gauss model gave the best performance of total inventory cost saving by more than 75% compared to stochastic EOQ model.

From the comparison in this study found that for the continuous data such as process control application, ANFIS model was appropriated to implement because of achieving the best performance of prediction accuracy and this model can reduce production defects. For discontinuous data such as inventory control application, FIS+ANFIS model was suitable to implement because of achieving the best performance of prediction accuracy and this model can reduce the inventory costs.

**Keywords**: Fuzzy Logic, Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Process Control, Inventory Control

# PUBLICATIONS

## International journal papers

Aengchuan, P., and Phruksaphanrat, B. (2015). Comparison of fuzzy inference system (FIS), FIS with artificial neural networks (FIS + ANN) and FIS with adaptive neuro-fuzzy inference system (FIS + ANFIS) for inventory control. **Journal of Intelligent Manufacturing**, 1-19. (Online) http://link.springer.com/article/10.1007/s10845-015-1146-1

## International conference papers

Aengchuan, P., and Phruksaphanrat, B. (2013). Inventory system design by fuzzy logic control: A case study. **Advanced Materials Research, 811**, 619-624.

Aengchuan, P., and Phruksaphanrat, B. (2013). Fuzzy Inventory System for Uncertain Demand and Supply. **The 3rd International Symposium on Engineering, Energy and Environments (ISEEE)**, Bangkok, Thailand: 17-23 November 2013.

Aengchuan, P., and Phruksaphanrat, B. (2015). Comparison of Fuzzy Inference System and Artificial Neural Network for Process Control. **The 4th International Symposium on Engineering, Energy and Environments (ISEEE)**, Thammasat University, Pattaya Campus, Thailand: 8-10 November 2015.

# ACKNOWLEDGEMENTS

I would like to express the most sincere appreciation and gratitude to my advisor, Associate Professor Dr. Busaba Phruksaphanrat for her continuous guidance, helpful advice and constant encourage throughout this study. I also express my sincerest gratitude to the committee members, Assistance Professor Dr. Apiwat Muttamara, Associate Professor Dr. Pongchanun Luangpaiboon, Associate Professor Dr. Sanya Mitaim and Dr. Wuttinan Nunkaew for their valuable counseling, helpful suggestion and kindly serving as members of the dissertation committee.

I am indebted to Valaya Alongkorn Rajabhat University under the Royal Patronage for having the scholarship to complete my study at Thammasat University. Furthermore, I would like to express the most appreciation to Faculty of Engineering, Thammasat University for supporting my research study.

Finally, I wish to thank my beloved parents and my wife, for their endless love, support and encouragement.

Prasert Aengchuan
Thammasat University
2015

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# CHAPTER 1
# INTRODUCTION

## 1.1 Brief significations and rationale of study

Nowadays, the manufacturing system's problems in the industry are more complex, according to the needs in various functions of the products. In several years, a lot of literatures presented the methods and tools for solving these problems. These methods mainly consist of three categories; operations research, simulation and artificial intelligence. The divisions among these three categories are fuzzy. For example, simulation is often considered to be operations research tool, while the mathematical programs of operations research are solved using search methods, studied in artificial intelligence (Chryssolouris, 2006).

Operation research mainly consists of mathematical programming, dynamic programming and queuing theory. Mathematical programming is a family of techniques for optimizing (minimizing or maximizing) a given algebraic objective function of a number of decision variables (Berry et al., 1979). The goal is to find the optimal solution, the point in feasible region. The mathematical programming comprises of linear programming, goal programming, and integer programming. Dynamic programming is a method for solving problems that can be viewed as multistage decision processes which can be separated into a number of sequential steps or stages that may be completed in one or more ways. Queuing theory is the study of the behavior of queuing systems through the formulation of analytical models. Queuing process consists of customers arriving at a service facility, then waiting in a line (queue) if all servers are busy, eventually receiving service, and finally departing from the facility (Keung et al., 2001).

Simulation is the generic name for a class of computer software, which simulates the operation of a manufacturing system. The inputs of the simulator are decision variables, which specify the design (e.g. machine processing and failure rates, machine layout), the workload (e.g. arrivals of raw materials over time, part routings), and the operational policy (e.g. "first come, first served") of a manufacturing system. The simulator assembles these data into a model of the manufacturing system. The user of simulator specifies the initial state (e.g. the number and types of parts initially in inventory at various points in the system). Then the simulator follows the operation of the model over time, tracking events such as parts movement, machine breakdowns, etc. over time. At the end of the simulation, the output provided by the simulator is a set of statistical performance measures by which the manufacturing system may be evaluated. Recently, Nagabhan and Smith, (2014) presented the literature review and analysis of simulation for manufacturing system design and operation.

Artificial intelligence (AI) is defined as the study of ideas that enable computers to be intelligent (Venkatarman and D'Itri, 2001). Its main goals are to make computers more useful, and to understand the principles that make intelligence possible. AI methods are mainly comprised of fuzzy logic, artificial neural network, adaptive neuro-fuzzy inference system (ANFIS), and generic programming. Applications of AI in various fields are getting more and more popular during the last decade and that is why much relevant research has been conducted (Kar et al.,2014).

For all three methods, operations research is the method that considers to deterministic input and output data and mathematical modeling is quite difficult and may not clearly understanding by industrial users, while simulation tools also difficult and construct via specialized simulation languages that required high expertise knowledge and involved with a lot of data generated. The AI tools are not complicated and more usefully applied methods for manufacturing system. So in this research, the AI tools such as fuzzy logic, ANN and ANFIS is selected to apply in the manufacturing system application.

The applications of AI are implemented in various sections of manufacturing system such as vehicles, robotic system, pneumatic system, cellular network, etc. For this study, the process control and inventory control are selected to study and compare among FIS, ANN and ANFIS.

For process control, the main objective is to provide the methods that are used to control process variables when manufacturing a product and maintain the output of a specific process within a desired range. Process control can be classified as manual or automatic. This division generally refers to the amount of human effort needed to achieve a common function. Manual control consists of open-loop and feed-forward control which involve a great deal of physical effort by the operator. Automatic control consists of closed-loop and feedback control, which employs a feedback path that samples the output to control the process automatically. Automatic feedback control is the most common form of control. The methods to deal with process control consist of classical and modern methods. The classical control methods such as on-off control, proportional integral derivative (PID) control, are mostly concerned with mathematical and constant variables. The modern control method such as artificial intelligence (AI) is developed for high complexity process and random variables. Process control is widely used in the industry such as power plants, petrochemical plants, cement plants, and many others. Process control enables automation and AI methods such as fuzzy logic, ANN, ANFIS and others by which a small staff of operating personnel can operate a complex process from a central control room. The applications of AI methods in manufacturing system have been reviewed and listed for their research methodologies. There are various applications of AI to manufacturing system and system modeling, but no application concerning to gypsum plaster manufacturing process. The gypsum plaster process is selected due to the output of process, which is plaster is the high quality product. The plaster products are used as the raw material for producing plasterboard of plasterboard plant or used as the finishing plaster for installation by users. The quality of the plaster is quite important for plasterboard plant. If plaster quality is not consistent, the quality of plasterboard is not good and become low quality products or wastes. The application of process control is proposed for comparison of FIS, ANN and ANFIS models.

For inventory control, the main purpose is to determine how much to order and when to order. Making decisions regarding the level of inventory is to balance between holding inventories and the cost associated with them. The inventory level is not easy to manage because of the factors involved and unpredicted events such as uncertainties of demand and supply. Inventory lot-sizing models have been reviewed and classified into three categories; deterministic, stochastic and fuzzy. Deterministic models assume known parameters which are not practical in the real world due to some uncertain parameters need to be considered. Stochastic models are effective when the input information is known and available, but in real situations, the supply may not exist when required due to their unpredictable events. For fuzzy models, fuzzy mathematical models are complicated and difficult to understand and implement while fuzzy logic models and adaptive neuro-fuzzy inference system (ANFIS) models are not complicated and more useful applied methods. Many researches focus on fuzzy mathematic and the fuzzy logic approach for inventory control, but there is limited published work regarding applications of the neuro-fuzzy approach to inventory based on fuzzy inference system (FIS) with artificial neural network (ANN) and FIS with ANFIS. Furthermore, consideration of both fuzzy demand and supply by ANN and ANFIS has not been taken into account.

## 1.2 Objectives of the research

This research aims to study and present the applications of FIS, ANN and ANFIS to industrial control for manufacturing system. The applications of process control and inventory control are selected for the study.

## 1.3 Scope of the research

The scope of this research is summarized as follows.

a) For process control application,

(1) To study and develop FIS, ANN and ANFIS models that are considered to process control of a case study factory.

(2) To compare FIS, ANN and ANFIS models for the prediction accuracy of the output of process control and waste reduction.

b) For inventory control application,

(1) To study and develop fuzzy inventory models that are considered for a singular product and type A of a case study factory.

(2) To compare FIS, FIS with ANN and FIS with ANFIS inventory models for the prediction accuracy and total inventory costs.

### 1.4 Assumptions and limitations

In this research, there are some assumptions and limitations described as follows.

a) For process control application, the study is a specific case of gypsum plaster factory. The process control data are collected from the data log sheet that recorded by the factory operators. Some of low effect parameters are assumed to be within a specific range. There are four input variables, which are roller mill current, blower hot air flow current, classifier speed and temperature. Output variable is combined water. Evaluation of methods is done by the defects of plasterboard production process.

b) For inventory control application, the study is a specific case of a furniture factory. Two input variables, uncertain supply and demand are considered. Lead time is considered as certain data and known for inventory model. Output variable is order quantity. Evaluation of methods is done by the total inventory costs.

### 1.5 Research methodology

According to the objectives mentioned earlier, the research methodology is divided into four major parts as following descriptions.

a) Study related contents of the fuzzy logic, FIS, ANN and ANFIS concerning to theories and literature review focused on production process parameters and inventory lot-sizing.

b) Construct FIS, ANN and ANFIS models for process control parameters by using MATLAB. The inputs, outputs and decision rule are based on each model.

c) Construct FIS, ANN and ANFIS models for inventory control by using MATLAB. The inputs, outputs and decision rule are based on each model. The evaluation algorithm is provided to consider the total inventory cost.

d) Compare all results by using performance parameters and present the best result with recommendation for each application approach.

The overall research methodology can be described in Fig. 1.1.

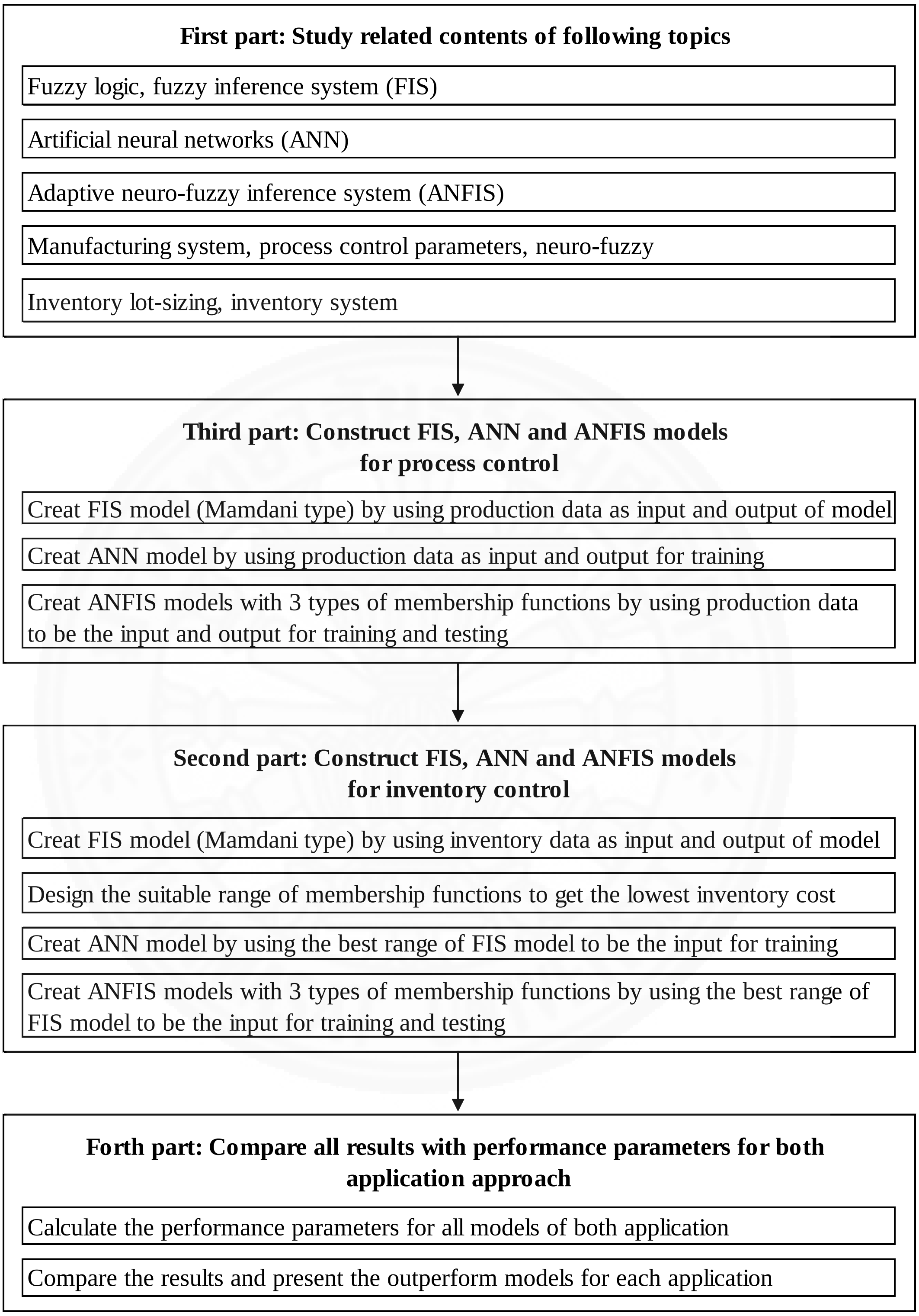



Fig. 1.1

The overall research methodology

### 1.6 Contributions of the research

This research makes both theoretical and practical contributions as follows.

a) Theoretical contributions: this research contributes to the literature on fuzzy logic, fuzzy inference system, artificial neural network and adaptive neuro-fuzzy inference system. For process control, the research proposes the suitable and not complicated method to adapt and use in the industrial application. This research is the first attempt to propose the comparison of FIS, FIS with ANN and FIS with ANFIS for inventory control system.

b) Practical contributions: the proposed method is applicable to the real-world of process control parameters and inventory control system in the industry. The benefit of the proposed method with outperform model could reduce waste from the production process and cost saving of the inventory control system.

### 1.7 The structure of this dissertation

The remainder of this dissertation is organized as follows. **Chapter 2** presents a review of the related theories and literatures. **Chapter 3** presents the research methodology for application of process control. **Chapter 4** provides the research methodology for application of inventory control. **Chapter 5** provides results and discussion for both applications. **Chapter 6** presents the overall conclusions of this dissertation and recommendations.

# CHAPTER 2
# THEORY AND LITERATURE REVIEW

In this chapter, the related theories and literatures are reviewed, i.e., fuzzy set, fuzzy logic, an artificial neural network, an adaptive neuro-fuzzy inference system and application in manufacturing system.

## 2.1 Fuzzy set

The concept of the fuzzy set is only an extension of the concept of a classical or crisp set. The fuzzy set is actually a fundamentally broader set compared with the classical or crisp set. The classical set only considers a limited number of degrees of membership, such as ‘0’ or ‘1’, or a range of data with limited degrees of membership (Bai and Wang, 2006). For example, the set of heights from 1.6 to 1.8 meters is crisp; the set of heights in the region around 1.7 meters is fuzzy. This means that the fuzzy set uses a universe of discourse as its base and it considers an infinite number of degrees of membership in a set. In this way, the classical or crisp set can be considered as a subset of the fuzzy set. A fuzzy set comprises elements which have varying degrees of membership in the set, and this is opposite to the classical or crisp sets due to members of a classical set cannot be members unless their membership is full or complete in that set. A fuzzy set permits a member to have a partial degree of membership and this partial degree membership can be mapped into a function or a universe of membership values. Suppose that we have a fuzzy set *A*, and if an element *x* is a member of this fuzzy set *A*, this mapping can be expressed as

$$\mu_A(x) \in [0, 1] \; (A = (x, \mu_A(x) | \, x \in X) \qquad (2.1)$$

A fuzzy subset *A* with an element, *x* has a membership function of $\mu_A(x)$. When the universe of discourse X is discrete and finite, this mapping can be represented as

$$A = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \dots = \sum_i \frac{\mu_A(x_i)}{x_i} \tag{2.2}$$

When the universe X is continuous and infinite, the fuzzy set $A$ can be expressed as

$$A = \int \frac{\mu_A(x)}{x} \tag{2.3}$$

## 2.2 Fuzzy logic

Fuzzy logic is frequently applied in our usual life. For example, to answer some survey questions, mostly we could answer with 'Quite Satisfied' or 'Not Very Satisfied', which are ambiguous or fuzzy answers. These vague answers can only be generated and performed by human beings, but not machines. It is definitely impossible for a computer to answer those survey questions directly as a human beings did. Computers can only know either '0' or '1', and 'True' or 'False'. Those data are defined as crisp or classic data and can be processed by all machines. The idea of fuzzy logic was invented by L. A. Zadeh in 1965. This invention was not well recognized until E. H. Mamdani, applied the fuzzy logic in a practical application to control an automatic steam engine in 1974 (Mamdani and Assilion, 1974). Then, more and more fuzzy implementations have been reported since the 1980s, including those applications in industrial manufacturing, automatic control, automobile production, banks, hospitals, and academic education. Fuzzy logic techniques have been widely applied in all aspects in today's society. To implement fuzzy logic technique to a real application requires the following three steps (Bai and Wang, 2006):

(1) Fuzzification – convert classical data or crisp data into fuzzy data or Membership Functions (MFs)

(2) Fuzzy Inference Process – combine membership functions with the control rules to derive the fuzzy output

(3) Defuzzification – use different methods to calculate each associated output

For example, to control a refrigeration system, the input temperature and the output control variables must be changed to the associated linguistic variables such as 'Low', 'Medium', 'High' and 'Slow', 'Medium', 'Fast'. The former is related to the input temperature and the latter is associated with the rotation speed of the operating motor. Normally both the input and the output must also be converted from crisp data to fuzzy data in first step – fuzzification. In the second step, the fuzzy inference process, the Membership Functions combine with the control rules to obtain the control outputs. The control rule is the important part of the fuzzy inference process, and those rules are directly associated to a human being's intuition and feeling. Different methods such as Center of Gravity (COG) or Mean of Maximum (MOM) are applied to compute the related control outputs. The next process is called defuzzification, the output is converted from the linguistic variable back to the crisp variable to control the operator. In most cases the input variables are more than one dimension for real applications, and one needs to perform fuzzification or develop a Membership Function for each dimensional variable independently. Perform the same operation if the system has multiple output variables. With the expeditious development of fuzzy technologies, different fuzzy control strategies have been developed based on different classical control methods, such as sliding-mode fuzzy control (Wu and Liu, 1996), neural fuzzy control, adaptor fuzzy control (Hsu and Fu, 2000) Currently, new fuzzy control strategies or combined crisp and fuzzy control techniques are being developed and will be applied to many areas.

### 2.2.1 Fuzzification and Membership Functions

The first step for utilizing a fuzzy inference system is fuzzification. Existing variables in the real world are mostly classical or crisp variables. Those crisp variables need to be converted to fuzzy variables for both input and output. Then the fuzzy inference is applied to process those data to get the required output. Finally, in most cases, those fuzzy outputs need to be converted back to crisp variables to achieve the required control outputs. Practically, fuzzification relates to two processes: originate the membership functions for input and output variables and express them with linguistic variables. This process is similar to mapping or converting a classical set to fuzzy set to changing degrees. In general, membership functions can have many different types, such as the triangular, trapezoidal, bell-shaped, Gaussian, S-curve and sigmoidal membership functions. The appropriate type depends on the actual applications. For those systems that need significant dynamic variation in a short period of time, a triangular or trapezoidal membership functions should be utilized. For those systems that need very high control accuracy, a Gaussian or S-curve membership functions should be selected.

### 2.2.2 Fuzzy control rules

Fuzzy control rule can be determined as the knowledge of an expert in any associated field of application. The fuzzy rule is described by a sequence of the form IF – THEN, directing to algorithms representing what action or output should be selected in terms of the presently observed information, which comprises both input and feedback if a closed-loop control system is utilized. The method to construct or design a set of fuzzy rules is depended on a human being's knowledge or experience, which is based on each different actual application. A fuzzy IF – THEN rule relates to a condition represented using linguistic variables and fuzzy sets to an output or a conclusion. This IF-THEN rule is widely utilized by the fuzzy inference system to calculate the degree to which the input data corresponds to the condition of a rule. For example in an application that uses two inputs for one output, some simple rules can be written as follows:

IF (temperature is LOW) AND (fan speed is NORMAL) THEN (result is COOL)

IF (temperature is NORMAL) AND (fan speed is HIGH) THEN (result is WARM)

IF (temperature is VERY LOW) AND (fan speed is HIGH) THEN (result is VERY COOL)

IF (temperature is VERY LOW) AND (fan speed is VERY HIGH) THEN (result is CRITICAL)

### 2.2.3 Defuzzification

The defuzzification process is denoted for converting the fuzzy output back to the crisp or classical output to the control objective. Actually, the fuzzy output is a linguistic variable and needs to be converted to the crisp variable via the defuzzification process. There are seven methods used for defuzzifying the fuzzy output as follows (Sivanandam et al., 2007):

(1) Max-membership principles or height method,
(2) Centroid method or center of gravity method,
(3) Weighted average method,
(4) Mean-max membership,
(5) Center of sums,
(6) Center of largest area, and
(7) First of maxima or last maxima

Three defuzzification methods are ordinarily used, which are: Mean-max method, Center of gravity method and the height method (Bai and Wang, 2006).

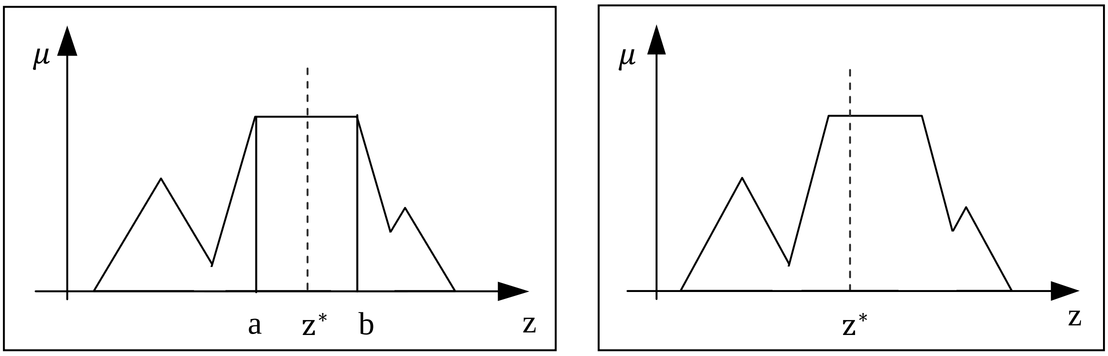
#### 2.2.3.1 Mean of Maximum (MOM) Method

The MOM defuzzification method or middle of maxima is associated to max-membership principle, but the existing of the maximum membership need not be unique, not be a single point, it can be range. This method is the average of those fuzzy outputs that have the highest degrees. The expression is given as

$$Z^* = \frac{a + b}{2} \tag{2.4}$$

where a, b are the end point of the maximum membership range as displayed in Fig. 2.1(a)

A deficiency of the MOM method is that it does not concern the whole shape of the output membership function, and it only considers the points that have the highest degrees in that function. For those membership functions that have different shapes, but the same highest degrees, this method will generate the same result.




(a) MOM method example (b) COG method example

Fig 2.1

Graphical representation of defuzzification techniques

**2.2.3.2 Center of Gravity (COG) Method**

The Center of Gravity method (COG) is the most well known defuzzification method and is vastly utilized in actual applications. The weighted average of the membership function or the center of the gravity of the area confined by the membership function curve is calculated to be the crispest value of the fuzzy quantity. It can be represented by the algebraic expression,

$$Z^{*} = \int \frac{\mu_A(z)zdz}{\mu_A(z)dz} \tag{2.5}$$

A graphical representation of the COG method is displayed in Fig. 2.1(b).

**2.2.3.3 The Height Method (HM)**

This defuzzification method is effective only for the case where the output membership function is an aggregated union result of symmetrical functions (Jamshidi et al., 1993). This method can be classified into two steps. First, the consequent membership function $F_i$ can be converted into a crisp consequent $z = f_i$ where $f_i$ is the center of gravity of $Z_i$. Then the COG method is utilized to the rules with crisp consequents, which can be expressed as

$$z^* = \frac{\sum_{i=1}^{M} w_i f_i}{\sum_{i=1}^{M} w_i} \tag{2.6}$$

where $w_i$ is the degree to which the $i^{th}$ rule corresponds the input data. The advantage of this method is its simplicity. Therefore many neuro-fuzzy models use this defuzzification method to reduce the complex of calculations.

### 2.2.4 Fuzzy inference system

Fuzzy inference system or fuzzy rule-based system is a system that is used to govern the relationship between the input and output variables of a system as shown in Fig. 2.2. There are three types of fuzzy inference systems: Mamdani-type, Sugeno-type and Tsukamoto-type. The main difference between Mamdani and Sugeno lies in the consequence of fuzzy rules. Mamdani-type uses fuzzy sets as a rule consequence, whereas Sugeno-type uses linear functions of input variables as rule consequence. For Tsukamoto-type, the consequent of each fuzzy rule uses a monotonical membership function. In this research Mamdani-type is used.

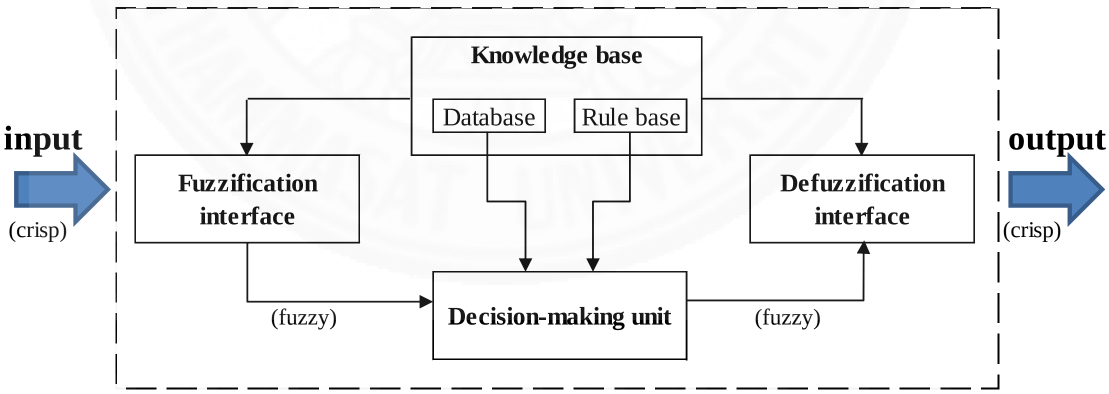



Fig. 2.2

A scheme of fuzzy inference system

In a fuzzy inference system, the crisp inputs are converted into fuzzy inputs by using fuzzification interface. After fuzzification the rule bases are formed.

The rule bases and the database are jointly referred to as the knowledge base. Defuzzification is used to convert the fuzzy value to the real world value which is the output. FIS is applied in many applications (Kovac et al. 2013; Nasrollahzadeh and Basiri 2014; Guner and Yumuk 2014; Camastra et al. 2015; Kocyigit 2015).

## 2.3 Artificial neural networks (ANN)

Artificial neural networks consist of a number of interlinked cells as neurons with weights, working together to initiate artificial intelligence or learning in machines. ANN consists of three layers: input, hidden and output layers. The input and output layers consist of a collection of neurons representing input and output variables. The hidden layer processes the data it receives from the input layer, and sends a response to the output layer. There is no theoretical limit on the number of hidden layers, but typically there is just one or two (Sumathi and Paneerelvam, 2010). The output layer accepts all responses from the hidden layer and produces an output vector. Each layer has a certain number of processing elements (neurons) which are linked with adjustable weights. These weights are adapted during the training process until the error is decreased greatly and is acceptable for a specific task. ANN is trained by a suitable algorithm for a particular problem. Although a number of training algorithms are available, the most popular is feed-forward, back propagation algorithm (Kiran and Rajput, 2011). The output of each neuron is calculated by multiplying its inputs by a weight vector, summing the results, and applying an activation function to the sum.

$$y = F\left(\sum_{k=1}^{l} w_k x_k + b_k\right) \tag{2.7}$$

where, $F$ is the activation function, $l$ is the number of neurons in the consecutive layer, $w_k$ is the weight of the respective connection, and $b_k$ is the bias for the neuron. $F$ is generally linear, step, threshold, logarithmic sigmoid (logsig) or hyperbolic tangent sigmoid (tansig) function. ANN is applied in many different applications (Esen et al. 2008a; Esen et al. 2008b; Esen et al. 2009; Yang and Zhou 2013; Kuo C. et al. 2014; Kuo R. et al. 2014; Tsai and Luo 2014; Jha et al. 2014; Kocyigit 2015; Wang et al. 2015).

**2.4 Adaptive neuro-fuzzy inference system (ANFIS)**

ANFIS unlike FIS, automatically produces adequate rules with respect to input and output data, and takes advantage of the learning capability of neural networks. It is presently one of the powerful tools used for pattern recognition, system identification and can create accurate models of systems. This approach does not require expertise for modelling and training a system.

Although various applications of the ANFIS have been applied (Azizi et al. 2013; Guneri et al., 2011; Melin et al., 2012), there are few researches applying inventory control in production systems. An ANFIS gives the mapping relationship between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions (Ying and Pan, 2008). In the ANFIS architecture, ANN learning algorithms are applied to determine the parameters of fuzzy inference system. A typical architecture of ANFIS is shown in Fig. 2.3 for modeling of function *f(x, y)*. The circular nodes represent nodes that are fixed, whereas the square nodes are nodes that have parameters to be learnt or called adaptive nodes. For simplicity, consider a FIS with two inputs (*x*, *y*) and one output (*f*). In addition, the rule base of FIS contains two fuzzy if-then rules of Takagi-Sugeno type. The two rules can be expressed as:

Rule 1: if x is $A_1$ and y is $B_1$, then $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is $A_2$ and y is $B_2$, then $f_2 = p_2x + q_2y + r_2$

where $A_i$, $B_i$ (i=1, 2) are fuzzy sets in the antecedent, and $p_i$, $q_i$, $r_i$ ($i$=1,2) are the design parameters that are determined during the training process.

Layer 1: Input nodes. Every node i in this layer is square node with a node function as equation (2.8):

$$O_i^1 = \mu_{A_i}(x),\ i = 1, 2 \qquad O_i^1 = \mu_{B_i}(y),\quad i = 1, 2 \tag{2.8}$$

where x, y are the crisp inputs of node i, and Ai, Bi are the linguistic labels characterized by membership functions, $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$, respectively.

Layer 2: Rule nodes. Every node in this layer represents the firing strength of a rule by multiplying the incoming signals and sending the product out as:

$$O_i^2 = \omega_i = \mu_{A_i}(x) \times \mu_{B_i}(y),\quad i = 1, 2. \tag{2.9}$$

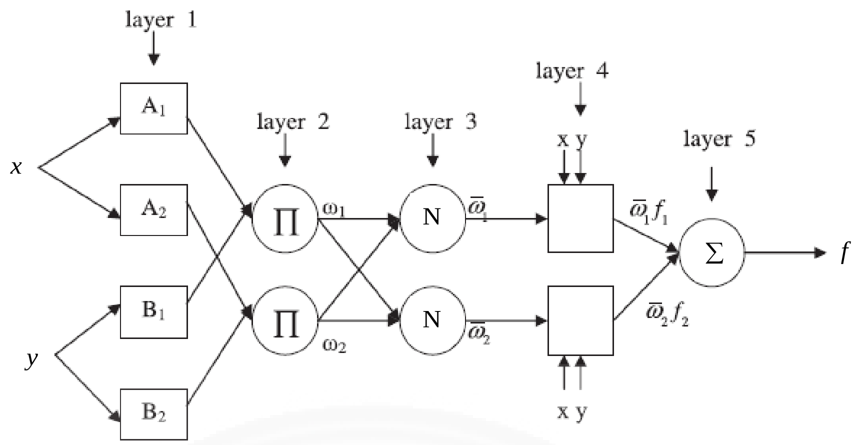



Fig 2.3

ANFIS architecture with two rules

Layer 3: Average nodes. The *i*-th node in this layer calculates the average ratio of the *i*-th rule's firing strength.

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}\ ,\ i = 1, 2 \tag{2.10}$$

where $\overline{\omega_i}$ is taken as the normalized firing strength.

Layer 4: Consequent nodes. The node function in this layer is represented by equation (2.11):

$$O_i^4 = \overline{\omega_i} f_i = \overline{\omega_i}(p_i x + q_i y + r_i), \quad i = 1, 2 \tag{2.11}$$

where $\overline{\omega_i}$ is the output of layer 3, and $\{p_i;\ q_i\ ;\ r_i\}$ is the parameter set. Parameters in this layer are referred to the consequent part of the Segeno fuzzy model.

Layer 5: Output nodes. The single node in this layer computes the overall output as the summation of all incoming signals. Accordingly, the defuzzification process transforms each rule's fuzzy results into a crisp output in this layer.

$$O_i^5 = \sum_{i=1}^{2} \overline{\omega}_i\, f_i = \frac{\overline{\omega}_1 f_1 + \overline{\omega}_2 f_2}{\overline{\omega}_1 + \overline{\omega}_2}\ , \quad i = 1, 2 \tag{2.12}$$

It is seen from the ANFIS architecture that when the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters:

$$f = (\overline{\omega_1} x) p_1 + (\overline{\omega_1} y) q_1 + (\overline{\omega_1}) r_1 + (\overline{\omega_2} x) p_2 + (\overline{\omega_2} y) q_2 + (\overline{\omega_2}) r_2 \tag{2.13}$$

ANFIS has a hybrid learning rule algorithm which integrates the gradient descent method and the least square methods to train parameters. In the forward pass of the algorithm, functional signals go forward until layer 4 and the consequent parameters are identified by the least squares method to minimize the measured error. In the backward pass, the premise parameters are updated by the gradient descent. ANFIS is applied in many applications (Hosoz et al. 2011; Chaudhary et al. 2014; Fragiadakis et al. 2014; Yang and Entchev 2014; Gokulachandran and Mohandas 2015).

## 2.5 Application in manufacturing system

The manufacturing system comprises of equipment, products, people, information, control and support functions for the competitive development to satisfy market needs. The term may refer to a range of human activity, from handicraft to high tech, but is most commonly applied to industrial production in which raw materials are transformed into finished goods on a large scale. The system model considers modeling the operation of an unknown system from a set of measured input, output data and has a wide range of applications in various areas such as control, power systems, communications, and machine intelligence (Kar et al, 2014).

The application in manufacturing system consists of many applications such as pneumatic system, robotic system, vehicles, cellular network, process control, maintenance management, etc. In this research, process control and inventory control have been selected to study and apply with FIS, ANN and ANFIS.

### 2.5.1 Process control

Process control refers to the methods that are used to control process variables when manufacturing a product and maintain the output of a specific process within a desired range. Process control can be classified as manual or automatic. Normally, this classification refers to the amount of human attempt needed to accomplish a common function. Manual control consists of open-loop and feed-forward control which involve a lot of physical attempts by the operator. Automatic control consists of closed-loop and feedback control, which uses a feedback path that samples the output to control the process automatically (Patrick and Fardo, 1997). Automatic feedback control is the most common form of control. The methods to deal with process control consist of classical and modern methods. The classical control methods such as on-off control, proportional integral derivative (PID) control, etc. are mostly concerned with mathematical and constant variables. The modern control method such as artificial intelligence (AI) is developed for high complexity process and random variables. Process control is widely used in the industry such as power plants, petrochemical plants, cement plants, and many others. Process control empowers automation and AI methods such as fuzzy logic, ANN, ANFIS and others by which a few working operators can control a complex process from a central control room. The applications of AI methods in manufacturing system have been reviewed and listed for their research methodologies.

During the last decade a number of researchers have contributed their innovations in this category. The contributions of AI reviewed according to methodologies, application descriptions and research types are shown in Table 2.1. Wang et al. (2004) presented a neuro fuzzy diagnosis system for monitoring gear function. Non-linear system has been analyzed (Chen et al., 2004) by applying the Takagi-Sugeno (T-S) fuzzy model to represent for the stability. This model extended to non-linear multiple time delay interconnected systems via the Lyapunov's direct method (Hsiao et al., 2005) and applied to non-linear structural systems (Chen, 2010) and further developed by using neural network, fuzzy control mechanism for time delay chaotic building system (Yeh et al., 2012). Kim et al. (2005) started working on underwater robots by applying neuro-fuzzy controller. The robot modeling and operation have further presented (Li et al., 2006; Vesselenyi et al., 2007) and also for mobile robot (Astudillo et al., 2006). Roy (2005) proposed an approach based on ANFIS for predicting surface roughness of the work piece in turning operation for set of cutting parameters mainly used in manufacturing and recently (Hossain and Ahanta, 2014) further studied for die manufacturing.

Ouyang et al. (2005) developed a TSK-type neuro-fuzzy technique for deriving the model from a given set of input-output data for system modeling problem. Kaitwanidvilai and Panichkun (2005) investigated two types of controller: adaptive neuro fuzzy model reference controller (ANFMRC) and hybrid ANFMRC to enhance the controller performance for pneumatic system. Yang et al. (2005) developed a neuro-fuzzy controller with self-organized optimal fuzzy rules and membership functions. Chen (2006) provided the stability conditions and controller design for a class of structural and mechanical systems represented by T-S fuzzy models. In 2008, Marza et al. aimed at building and evaluating a neuro-fuzzy model to estimate software projects developers. Topalov et al. (2009) presented by using a new neuro-fuzzy adaptive control approach for development of anti-breaking system and further developed (Tapalov et al., 2011; Abiyev et al., 2011). Sayedhoseini et al. (2010) developed an approach based on ANFIS for measurement of agility in supply chain management. Kurnaz et al. (2010) presented ANFIS for autonomous flight controller for UAVs (unmanned aerial vehicles). Mahdaoui et al. (2012) used neuro-fuzzy diagnosis approach along with TSK/Mamdani model and pattern recognition technique in manufacturing system. Kayacan et al. (2012) modeled intelligent control of tractor implement system by using type 2 fuzzy neural network. Abghari and Sadi (2013) presented the application of ANFIS to predict the yield distribution of main products in the steam cracking of atmospheric gasoil. Zhou et al. (2013) applied ANFIS for operational problem solving in a $CO_2$ capturing process system. Shamshirband et al. (2014) developed the methods by using FL, ANN and ANFIS for wind turbine wake models. Ozkan and Inal (2014) presented the comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems. Pani and Mohanta (2014) presented the application of support vector regression, fuzzy inference and adaptive neuro-fuzzy inference techniques for online monitoring of cement fineness. Petkovic et al. (2014) developed the adaptive neuro-fuzzy estimation of optimal lens system parameters. Recently Al-Ghamdi and Taylan (2015) proposed a comparative study on modeling material removal rate by ANFIS and polynomial methods in the electrical discharge machining process.

Table 2.1

The contributions of AI in manufacturing system

| | Author | Methodology | | | | | | | Application description | Research type |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Fuzzy | | | ANN | ANFIS | Hybrid | Other | | |
| | | FL | T-S | T2 FL | | | | | | |
| 1 | Wang et al. (2004) | x | | | x | | | | Gear industry | Industrial context |
| 2 | Chen et al. (2004) | | x | | | | | x | Nonlinear systems | Simulation |
| 3 | Kim et al. (2005) | x | | | x | | | | Underwater robotics | Simulation |
| 4 | Roy (2005) | | | | | x | | | Surface roughness | Comparison |
| 5 | Ouyang et al. (2005) | | x | | x | | | | System modeling | Experimental |
| 6 | Kaitwanidvilai and Panichkun (2005) | | | | | | x | | Pneumatic system | Industrial context |
| 7 | Yang et al. (2005) | x | | | x | | | | Electrical plant | Experimental |
| 8 | Hsiao et al. (2005) | | x | | | | | | Nonlinear time delay systems | Case study |
| 9 | Li et al. (2006) | x | | | x | | | | Robot modeling | Simulation |
| 10 | Astudillo et al. (2006) | | | x | | | | | Mobile robot | Simulation |
| 11 | Tettey and Marwala (2006) | | x | | | | | | Conflict management | Demonstrating |
| 12 | Chen (2006) | | x | | | | | | Stability conditions | Simulation |
| 13 | Vesselenyi et al. (2007) | x | | | x | | | x | Robotic grinding operation | Experimental |
| 14 | Marza et al. (2008) | x | | | x | | | | Software development | Estimation |
| 15 | Topalov et al. (2009) | | | | x | | | x | Anti breaking system | Simulation |
| 16 | Seyedhoseine et al. (2010) | | | | | x | | | Supply chain management | Case study |
| 17 | Kurnaz et al. (2010) | | | | | x | | | Unmanned flight control | Simulation |
| 18 | Chen (2010) | | x | | | | | x | Nonlinear structural systems | Simulation |
| 19 | Topalov et al. (2011) | x | | | x | | | x | Anti breaking system | Simulation |
| 20 | Abiyev et al. (2011) | | | x | x | | | | Time varying system | Simulation |
| 21 | Mahdaoui et al. (2012) | | x | | x | | | | Manufacturing | Diagnosis |
| 22 | Kayacan et al. (2012) | | | x | x | | | | Tractor industry | Simulation |
| 23 | Yeh et al. (2012) | | x | | x | | | | Time delay system | Development |
| 24 | Abghari and Sadi (2013) | | | | | x | | | Atmosheric gasoil | Experimental |
| 25 | Zhou et al. (2013) | | | | | x | | | $CO_2$ capturing process | Development |
| 26 | Shamshirband et al. (2014) | x | | | x | x | | | Wind turbine | Simulation |
| 27 | Özkan and Inal (2014) | | | | x | x | | | Multi-criteria decision making | Comparison |
| 28 | Subbaraj and Kannapiran (2014) | | | | x | x | | | Fault detection of pneumatic valve | Simulation |
| 29 | Pani and Mohanta (2014) | x | | | x | x | | x | Soft sensing of particle size in a grinding process | Simulation |
| 30 | Hossain and Ahmad (2014) | | | | x | x | | | Cutting parameters of die manufacturing | Experimental |
| 31 | Petkovic et al. (2014) | | | | | x | | | Lens system parameters | Optimization |
| 32 | Al-Ghamdi and Taylan (2015) | | | | | x | | x | Electrical discharge machining process | Comparison |

Note:

**Methodology:** FL = Fuzzy Logic, T-S = Takagi-Sugeno, T2 FL = Type 2 Fuzzy Logic, ANN = Aritificial Neural Network, ANFIS = Adaptive Neuro-Fuzzy Inference System, Hybrid = Hybrid Adaptive Neuro-Fuzzy

### 2.5.1.1 Gypsum plaster manufacturing process

Gypsum ($CaSO_4 \cdot 2H_2O$) is one of the oldest inorganic materials and has been widely used in buildings and constructions. Gypsum products are generally produced by the calcining process. Plaster or hemihydrate ($CaSO_4 \cdot 0.5H_2O$) has produced by grinding and heating gypsum at 150 $^{\circ}$C to remove 75% of its combined water from 2 molecules of water to be 0.5 molecules of water. This reaction is called cacination and written as $\mathrm{CaSO_4 \cdot 2H_2O \rightarrow CaSO_4 \cdot 0.5H_2O + 1.5H_2O}$.

The flow diagram of the plaster manufacturing process is shown in Fig. 2.4. From this process, the natural gypsum is crushed and fed into a vertical roller mill (VRM). The schematic diagram of VRM is shown in Fig. 2.5. The gypsum has ground and dried inside the VRM to be the plaster powder. VRM is consists of a grinding table with grinding rollers fitted on the table periphery. The grinding table rotates with certain fixed rpm about the axis passing through the center and perpendicular to it. An induced draft fan operates at the process outlet to carry plaster by air to the subsequent section. A classifier is arranged at the top of the mill to screen the required particle size. The coarse size is collected at the bottom and circulated back to the mill by use of bucket elevators. The plaster is separated from the carrier gas in the bag house and sent to the storage silo for subsequent packaging or producing plasterboard. The quality of the plaster is tested by collecting the plaster sample at silo to test the combined water (*CW*).

The combined water indicates the percentage of water remaining in the chemical bonding of plaster. Normally, combined water is tested by weighing the collected plaster sample before and after heating at 150 C for 15 minutes. The combined water value can be calculated as

$$CW(\%) = \frac{(w_0 - w_i)}{w_0} \times 100 \tag{2.14}$$

where $w_0$ is the sample weight before heating, and $w_i$ is the sample weight after heating.

The target *CW* for the plaster production process, recommended by expert's experience, is 5.8% and the variation is controlled by range 5.6% to 6.0%. Low combined water indicates too much cooked of the plaster or less water in the plaster. High combined water indicates rarely cooked of the plaster or high water in the plaster. The main factors influencing the plaster quality are: the gypsum feeding rate, air circulation rate, the classifier operating speed and temperature inside the mill. Lower feeding rate of gypsum will affect more effective grinding and indicated by lower of the roller mill motor current and will result in increase of combined water. High feeding rate of gypsum will affect less effective grinding and will result in decrease of combined water. Likewise, low air circulation rate will affect less quantity of ground material passed through the classifier and result in increase of combined water. High air circulation rate will affect high quantity of ground material passed through the classifier and result in decrease of combined water. A high classifier speed will allow fine particles to pass through it and will result in increase of combined water. A low classifier speed will result in decrease of combined water. High temperature inside the mill cause by more heat for cooking of grinding gypsum and will result in decrease of combined water. Low temperature inside the mill cause by less heat for cooking and will result in increase of combined water.

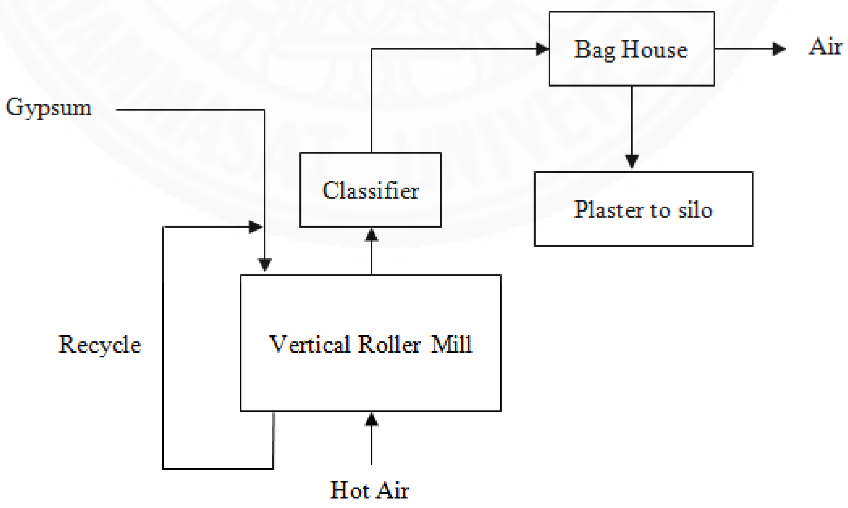



Fig. 2.4

Plaster grinding process in the gypsum plaster production process

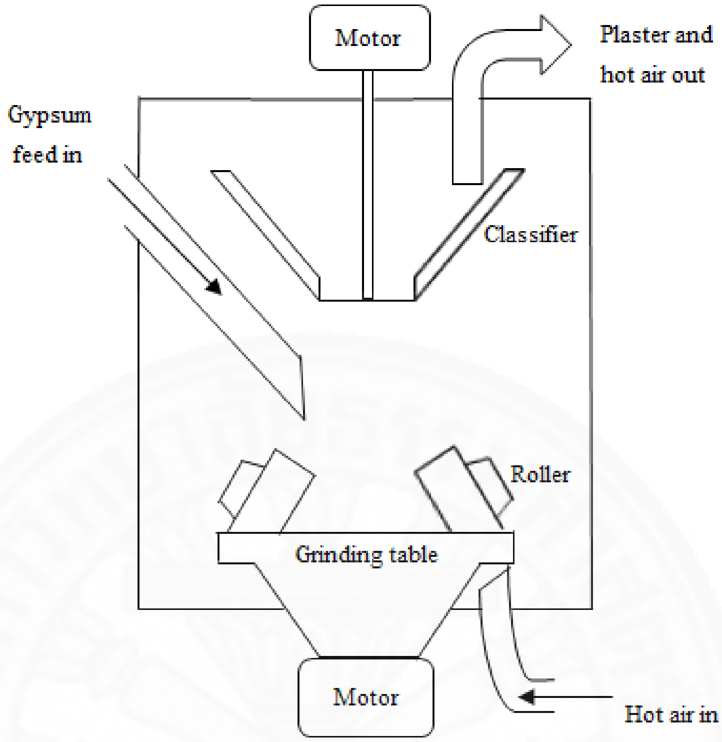



Fig. 2.5

Schematic diagram of the vertical roller mill

### 2.5.2 Inventory control

An inventory system controls the level of inventory by determining how much to order (the level of replenishment) and when to order (reorder point). The objective of an inventory system is to make decisions regarding the level of inventory that will result in a good balance between holding inventories and the cost associated with them. The inventory level is not easy to manage because of the number of factors involved and unpredictable events such as uncertainties of demand and supply. A suitable control system and policy for each type of product is necessary.

#### 2.5.2.1 Inventory lot-sizing

Inventory lot-sizing problems are production planning problems with the objective of determining the periods when production should take place and the quantities to be produced in order to satisfy demand while minimizing production and inventory costs. Since the original lot-sizing model presented by Harris in 1913 (Andriolo et al., 2014), most models focus mainly on deterministic static lot-sizing models. Further work (Sommer, 1981; Samanta and Al-Araimi, 2001) has developed fuzzy lot sizing models, followed by adaptive neuro-fuzzy inference system (ANFIS) (Samanta and Al-Araimi, 2003) to fuzzy inventory lot-sizing models. Recently, several literature reviews of lot-sizing models have been presented (Andriolo et al., 2014; Aluolou et al., 2014; Glock et al., 2014).

Inventory lot-sizing models can be classified into three categories which are deterministic models, stochastic models and fuzzy models as illustrated in Fig. 2.6. Table 2.2 shows the contributions of the inventory lot-sizing models.

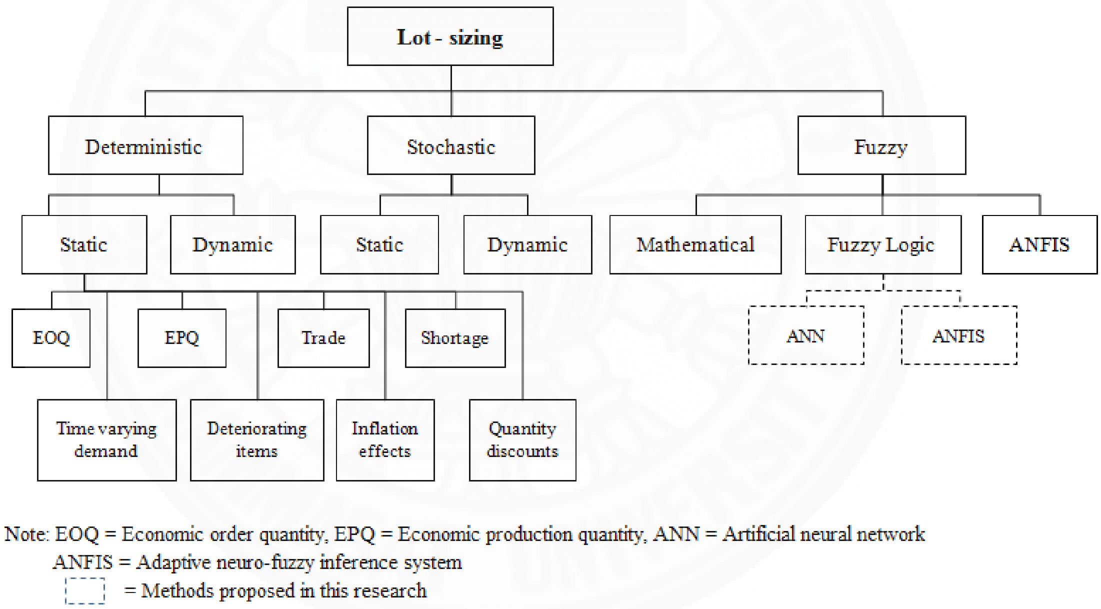



Fig. 2.6
Classification of inventory lot-sizing models

**(1) Deterministic lot-sizing models**

All input data of deterministic lot-sizing models are assumed to be available. These models can be divided into two groups, static and dynamic models. For deterministic static lot-sizing models, the original model was known as Economic Order Quantity (EOQ) or square root formula, with the objective to minimize the sum of ordering and inventory holding costs. The EOQ formula was modified (Taft, 1918) by adding a ratio between demand rate and production capacity and called Economic Production Quantity (EPQ). Since then many extended researches about EOQ and EPQ have been reported.

For deterministic dynamic lot-sizing models, the goal is to minimise the sum of setup costs and inventory holding costs, but it allows the demand for products to vary over time.

Because the deterministic models assume known parameters, most of the existing literature tries to give an optimal solution of the problem while others give some heuristic approaches in order to gain good results for practical situations. However, in the real world, there are some uncertain parameters that need to be considered.

**(2) Stochastic lot-sizing models**

Some input data of stochastic lot-sizing models are defined as probability density functions. These models can be divided into two groups, static and dynamic models. Many stochastic static lot-sizing models are based on the EOQ model, but have different stochastic information such as lead time, demand, supplier capacity, cost, price etc. Heuristic methods (Seneyigit and Erol, 2010) for stochastic lot-sizing and EPQ models for deteriorating inventory (Chung et al., 2011; Wee and Widyadana, 2012) have been proposed.

Dynamic stochastic lot-sizing models were presented to solve the problem of uncertain demand (Kamal and Sculfort, 2007) and normally can be solved by the optimization models such as the Wagner-Whitin (WW) algorithm and the heuristic models such as Silver-Meal (SM) method, part period balancing (PPB), lot for lot (L4L) etc. On the basis of probability theory, stochastic inventory models are effective when the input information of models is known exactly and is available (Chen, 2011). In a real world situation, supply data may not exist when required because of random capacity of suppliers, unpredictable events or seasonal factors. Meanwhile, some of the uncertainties within the inventory system cannot be taken into account properly by using concepts of probability theory (Tanthatemee and Phruksaphanrat, 2012).

Table 2.2

The contributions of the inventory lot-sizing models

| | **Author** | **Lot sizing models** | | | | | | | **Parameters** | | | | | | | | **Method/Keywords** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Det. | | Sto. | | Fuzzy | | | Demand | | Supply | | Leadtime | | Other | | |
| | | S | D | S | D | MA | FL | AN | C | U | C | U | C | U | C | U | |
| 1 | Harris (1913) | x | | | | | | | x | | x | | x | | x | | original EOQ formula (square root formula) |
| 2 | Taft (1918) | x | | | | | | | x | | x | | x | | x | | add ratio between demand rate and production capacity (EPQ) |
| 3 | Wagner and Whitin (1958) | | x | | | | | | x | | x | | x | | x | | optimization method, dynamic programming, difficult to understand and more computation effort |
| 4 | Silver and Meal (1973) | x | | | | | | | x | | x | | x | | x | | heuristic for time varying demand rate |
| 5 | Sommer (1981) | | | | | x | | | x | | x | | x | | | x | fuzzy dynamic programming for production scheduling with capacity constraints |
| 6 | Porteus (1986) | | | x | | | | | x | | x | | x | | | x | process deterioration "out of control" uncertain of process |
| 7 | Park (1987) | | | | | x | | | x | | x | | x | | | x | fuzzy cost (holding and ordering cost) |
| 8 | Parlar and Perry (1995) | | | | | x | | | x | | | x | x | | x | | Markov chain for uncertain supply |
| 9 | Chen et al. (1996) | | | | | x | | | | x | x | | x | | | x | fuzzy demand, fuzzy cost (ordering, inventory and backorder) |
| 10 | Lee and Yao (1999) | | | | | x | | | | x | x | | x | | | x | fuzzy demand rate, fuzzy production rate |
| 11 | Samanta and Al-Araimi (2001) | | | | | | x | | | x | x | | x | | x | | fuzzy logic control with fuzzy demand |
| 12 | Mondal and Maiti (2002) | | | | | x | | | | x | x | | x | | | x | genetic algorithm for multi-item fuzzy demand and inventory cost |
| 13 | Samanta and Al-Araimi (2003) | | | | | | | x | | x | x | | x | | | x | ANFIS, fuzzy logic control for fuzzy demand and inventory level |
| 14 | Yimer and Demirli (2004) | | | | | | x | | | x | x | | x | | x | | fuzzy simulation for variable demand and uncertain lead time |
| 15 | Rothstein and Rakityanskaya (2006) | | | | | | x | | | x | x | | x | | | x | fuzzy logic model for inventory control of fuzzy demand and stock |
| 16 | Kamal and Schulfort (2007) | | | | | | x | | | x | x | | | x | x | | demand and lead time uncertainties |
| 17 | Hanfield et al. (2009) | | | | | x | | | | x | x | | | x | | x | fuzzy model for uncertain demand, lead time, supplier yield and penalty cost |
| 18 | Rong (2010) | | | x | | | | | x | | x | | x | | | x | stochastic cost (ordering cost, holding cost and purchasing cost) |
| 19 | Khan et al. (2010) | | | x | | | | | x | | x | | x | | | x | mathematical for imperfect quality items, defective rate with learning effects |
| 20 | Wang (2010) | | | | | x | | | x | | | x | x | | x | | mathematical for uncertain supply |
| 21 | Seneyigit and Erol (2010) | | | x | | | | | | x | x | | x | | | x | demand and price uncertainties with service-level constraint |

Table 2.2

(continued)

| | Author | Lot sizing models | | | | | | | Parameters | | | | | | | | Method/Keywords |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Det. | | Sto. | | Fuzzy | | | Demand | | Supply | | Leadtime | | Other | | |
| | | S | D | S | D | MA | FL | AN | C | U | C | U | C | U | C | U | |
| 22 | Feng (2010) | | | | x | | | | x | | | x | | | | x | dynamic pricing and decisions under supply capacity uncertainty |
| 23 | Sana (2011) | | | x | | | | | | x | x | | x | | | x | randome sales price |
| 24 | Chung et al. (2011) | | | x | | | | | x | | x | | x | | | x | random unavailability of maintenance time |
| 25 | Guan (2011) | | | | x | | | | | x | x | | x | | | x | dynamic programming with time varying capacity constraint |
| 26 | Wee and Widyadana (2012) | | | x | | | | | x | | x | | x | | | x | stochastic preventive maintenance time |
| 27 | Guillaume et al. (2012) | | | | | x | | | | x | x | | x | | | x | fuzzy demand to find robust procurement plan |
| 28 | Chede et al. (2012) | | | | | | x | | | x | x | | x | | | x | fuzzy logic for inventory control with fuzzy demand and stock on hand |
| 29 | Tanthatemee and Phruksaphanrat (2012) | | | | | | x | | | x | | x | x | | x | | fuzzy logic for inventory control with fuzzy demand and supply |
| 30 | Lenart et al. (2012) | | | | | | | x | | x | x | | x | | | x | ANFIS to find the optimal storage level and cost with fuzzy demand and feedback information |
| 31 | Kang and Lee (2013) | | | | x | | | | | x | x | | x | | | x | mix integer programming and heuristic dynamic programming for mulitiple suppliers, quantity discount and safety stocks |
| 32 | Mahata and Gosmawi (2013) | | | | | x | | | | x | x | | x | | | x | fuzzy models for items with imperfect quality and shortage backordering under crisp and fuzzy decision variables |
| 33 | Aengchuan and Phruksaphanrat (2013) | | | | | | x | | | x | | x | x | | x | | fuzzy logic design range for inventory control with fuzzy demand and supply |
| 34 | Grubbstrom (2014) | | x | | | | | | x | | x | | x | | x | | dynamic EPQ model with net present value (NPV) |
| 35 | Li and Thorstenson (2014) | | | | x | | | | | x | x | | x | | | x | joint lot-sizing, pricing of stochastic demand and capacity constraints |
| 36 | Lee et al. (2014) | | | x | | | | | | x | x | | x | | x | | random demand, transient shortage during production stage |
| 37 | Ullah and Kang (2014) | x | | | | | | | x | | x | | x | | x | | mathematical model for work in process inventory |

Note:

**Lot sizing models**: Det. = Deterministic, Sto. = Stochastic, S = Static, D = Dynamic, MA = Mathematical, FL = Fuzzy Logic, AN = ANFIS

**Parameters**: C = Certain, U = Uncertain

**(3) Fuzzy lot-sizing models**

Fuzzy set theory has been applied to inventory problems with uncertainties in non-stochastic sense. These models can be divided into three groups, mathematical, fuzzy logic and ANFIS models.

For fuzzy mathematical lot-sizing models, many models of fuzzy EOQ models have been proposed. Many researches applied fuzzy sets to demand, deterioration rate, defective rate, lead time, etc, but many of these methods are complicated and difficult to implement.

Fuzzy logic lot-sizing models have been presented (Samanta and Al-Araimi, 2001) for fuzzy demand. A fuzzy simulation of a single item inventory system with variable demand to evaluate the EOQ with uncertain lead time (Yimer and Demirli, 2004) was developed. Other fuzzy logic models considered inventory control of fuzzy demand and stock (Rothstein and Rakityanskaya, 2006; Chede et al., 2012) and also demand and lead time uncertainties by fuzzy logic (Kamal and Schulfort, 2007). A fuzzy continuous inventory control system for a single item with both uncertain demand and supply has been presented (Tanthatemee and Phruksaphanrat, 2012) and later determination of the design range and the effect of trend demand (Aengchuan and Phruksaphanrat, 2013). This model saved inventory costs greatly when compared with the conventional stochastic EOQ model, Silver Meal model and Wagner Whitin Model.

For ANFIS lot-sizing models, adaptive neuro-fuzzy inference system and fuzzy logic control have been proposed for fuzzy demand and inventory level (Samanta and Al-Araimi, 2003). The ANFIS approach to adaptive inventory control has been applied to single input – single output (Lenart et al., 2012). The set of input values were determined by the expected values of the demand.

Fuzzy mathematical models are complicated and difficult for decision makers to implement in real life situations but fuzzy logic tools are not complicated to implement and modify. However, fuzzy tools should achieve the same as or better than other soft approaches to decision making under uncertainties (Azedegan et al., 2011). These characteristics have made fuzzy logic and tools associated with its use quite popular in tackling manufacturing related challenges. Many researches focus on a fuzzy mathematical and fuzzy logic approach for inventory system, but there is limited published work regarding applications of the neuro-fuzzy approach to inventory based on FIS+ANN and FIS+ANFIS. Furthermore, consideration of both fuzzy demand and supply by ANN and ANFIS has not been taken into account.

#### 2.5.2.2 Inventory system

The relevant elements associated with how much to order are normally concerned with inventory costs and inventory lot-sizing models. The inventory cost consists of holding cost, ordering cost and shortage cost. All inventory models try to reduce the total inventory costs.

**(1) Inventory cost**

In making any decision with respect to inventories, the following costs must be considered

Ordering cost is the fixed costs usually associated with the production of a lot internally or the placing of an order externally with a vendor.

Holding (or carrying) cost includes the costs for storage, handling, insurances, pilferage, breakage, obsolescence.

Shortage cost. This is usually the sum of the lost profit. It occurs when customer demand cannot be met because of insufficient inventory. There is a trade-off between carrying stock to satisfy demand and the costs resulting from stock out.

The case study model considers the total inventory costs as the summation of ordering cost, holding cost and shortage cost.

$$TC = mC_o + C_hQ_h + C_sQ_s \tag{2.15}$$

where,
$TC$ : Total cost.
$m$ : Number of ordering per period.
$C_o$ : Ordering cost per time.
$C_h$ : Holding cost per unit per period.
$C_s$ : Shortage cost per unit per period.
$Q_h$ : Holding quantity per period.
$Q_s$ : Shortage quantity per period.

**(2) Static inventory lot-sizing**

In a continuous or fixed-order-quantity system when inventory reaches a specific level, referred as the reorder point, a fixed amount is ordered. The EOQ model is extended to the stochastic EOQ model to solve the problem of uncertain demand, and is used when the uncertainties are considered as random that can handled by probability theory. Assuming that the demand is represented by a normal distribution, determination of how much to order can be calculated (Kamal and Sculfort, 2007) by the following equation.

$$Q^* = EOQ = \sqrt{\frac{2C_o H \bar{d}(C_h + C_s)}{C_h C_s}} \quad , \tag{2.16}$$

where $\bar{d}$ : Average weekly demand.

$H$ : Total length of the planning horizon (number of weeks).

If demand is uncertain, safety stock must be added into the reorder point and the reorder point and the safety stock can be computed.

$$R = \bar{d}L + SS \, , \tag{2.17}$$

$$SS = z\sigma_d \sqrt{L} \, , \tag{2.18}$$

where $R$ : Unit of reorder point.

$SS$ : Safety stock.

$L$ : Lead time.

$\sigma_d$ : The standard deviation of weekly demand.

$z$ : The number of standard deviations according to the service level probability.

**(3) Dynamic Inventory Lot-sizing Models**

Dynamic inventory lot-sizing models consist of two simple rule methods, heuristic methods and optimization methods. The classical dynamic lot sizing methods consist of Silver-Meal (Silver and Meal, 1973), Wagner-Whitin (Wagner and Whitin, 1958), Part-Period Balancing (DeMatteis, 1968), Least Unit Cost, Economic Order Interval, MacLauren’s Order Moment (Vollmann et al., 1997)

Groff's Algorithm (Groff, 1979). The most popular methods are Silver-Meal (SM) and Wagner-Whitin (WW). SM is an optimization method by selecting the order that minimizes the cost per period whereas WW method provides a dynamic programming solution algorithm and structural results on the optimal solution (Toy and Berk, 2013).

The Silver Meal (SM) was proposed by Sipper and Bulfin in 1973. It tries to obtain the minimum average cost per period for the *m* period span. The future demand for the next *n* periods is given as $D_1, D_2, \ldots, D_n$.

Let $K(m)$ be average variable cost per period if the order covers *m* periods. The general form of $K(m)$ is

$$K(m)=\frac{1}{m}(C_o+C_hD_2+2C_hD_3+\ldots+(m\text{-}1)C_hD_m). \tag{2.19}$$

Calculate $K(m)$, $m = 1,2,\ldots, m$, and stop when $K(m + 1) > K(m)$ i.e., the period in which the average cost per period starts increasing. We order in the period 1 a quantity to meet the demand of the next *m* periods, i.e.,

$$Q_1 = D_1 + D_2 + \ldots + D_m. \tag{2.20}$$

WW algorithm (Sipper and Bulfin, 1998) is the optimal model for finding the optimal order quantity, $Q_i$ for a dynamic inventory lot-sizing model. The objective is to minimize the variable inventory cost, ordering cost and holding cost over the planning horizon. The optimal order quantities satisfy

$$Q_i = \sum_{k=1}^{j} D_k \quad \text{for some } j > i. \tag{2.21}$$

$Q_i$ is the number of units, ordered in a period *i* to cover demand through period *j*, with the next order placed at period $j+1$. Let $K_{t,l}$ be the cost to place an order to cover the demand in period $t$, $t+1,\ldots, l$, assuming zero inventory at the beginning of period *t* and zero inventory at the end of period *l*. Mathematically, this cost is

$$K_{t,l} = C_o + C_h\left(\sum_{j=t+1}^{l}(j-t)D_j\right),\ t = 1, 2, \ldots, n;\ l = t+1, t+2, \ldots,n. \tag{2.22}$$

The equation for the minimum can be found recursively, Let $K_l^*$ denotes this minimum in period *l*, and it is given by

$$K_l^* = \min_{t=1,2,\dots,l} \left\{K_{l-1}^* + K_l^*\right\}, \quad l=1, 2, \dots, N. \tag{2.23}$$

$K_0^*$ is defined as zero, and the least-cost solution value is given by $K_N^*$.

## 2.6 Performance parameters

The performance of the models can be verified with the following statistical functions: the coefficient of determination ($R^2$), the root mean squared error (*RMSE*) and the mean absolute error (*MAE*) as described in equations (2.24), (2.25) and (2.26).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(A_i - P_i\right)^2}{\sum_{i=1}^{n}\left(A_i - \overline{A}_i\right)^2} \tag{2.24}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(A_i - P_i\right)^2}{n}} \tag{2.25}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|A_i - P_i\right|}{n}, \tag{2.26}$$

where $P_i$ : Predicted values.
$A_i$ : Observed values.
$\overline{A}_i$ : The average of observed set.
$n$ : Number of datasets.

$R^2$ represents how much the variability in dependent variables can be explained by independent variables. $R^2$ can have a value between zero and one. A value for $R^2$ close to one shows a good fit of predicting model and a value close to zero shows a poor fit. *MAE* would reflect if the results suffer from a bias between the actual and modeled datasets. *RMSE* is a measure used to calculate the difference between values predicted by a model and the values observed from the item being modeled. *RMSE* and *MAE* are non-negative numbers with no upper bound and can be zero only for an ideal model.

### 2.7 K-fold cross validation

K-fold cross validation is a certified method, presented to test generalization capability of ANN methods (Good, 1999). This method was utilized for further evaluation of the proposed models efficiency. The data set is divided into *k* subsets, and then repeated *k* times for running with the model. Each time, one of the *k* subsets is used as the test set and the other *k*-1 subsets are put together to be a training set. Then the average error across all *k* trials is calculated. The advantage of this method is that it matters less how the data gets divided. Every data point gets to be in a test set exactly once, and gets to be in a training set *k*-1 times. The variance of the resulting estimate is reduced as *k* is increased. The disadvantage of this method is that it consumes k-times calculation to make an evaluation.

# CHAPTER 3
# RESEARCH METHODOLOGY FOR PROCESS CONTROL APPLICATION

Process control is a main function in manufacturing system, which affect to production efficiency for the factory. This chapter introduces the models of FIS, ANN, and ANFIS for process control for a plasterboard factory which has uncertain process control parameters. These models are compared and discussed in the following subsections.

## 3.1 Application for process control

The process control problem of a construction material company in Thailand has been selected as a manufacturing system case study. The company is a made-to-stock manufacturer that produces two types of standard size plasterboard products, recess edge and square edge. For production process, the main material is plaster powder which is generally produced by the calcining process.

All input data from January 2015 to May 2015 were collected from the plant and shown in Fig. 3.1. From Fig. 3.1, it can be noticed that the input parameters of VRM process control are extremely fluctuated and caused the inconsistency of output quality or combined water. The output data or actual combined water were also collected from the same period in each month and shown in Fig. 3.2. From Fig. 3.2, the combined water data are exceedingly fluctuated. The inconsistency of combined water will result in plasterboard production process and cause the defects of finished goods. Normally, the cause of inconsistency of combined water of plaster will result in board setting and board forming of plasterboard process. The defects during this process need to be rejected to be the wet waste boards or scraps. The percentage of defective products collected in each month is shown in Fig. 3.3. The problem of plasterboard setting will result in the drying process in the dryer and may cause paper peeling that can be obstructed inside the dryer. Meanwhile, the inconsistency of plaster quality will extremely affected to plasterboard production defects of the plant.

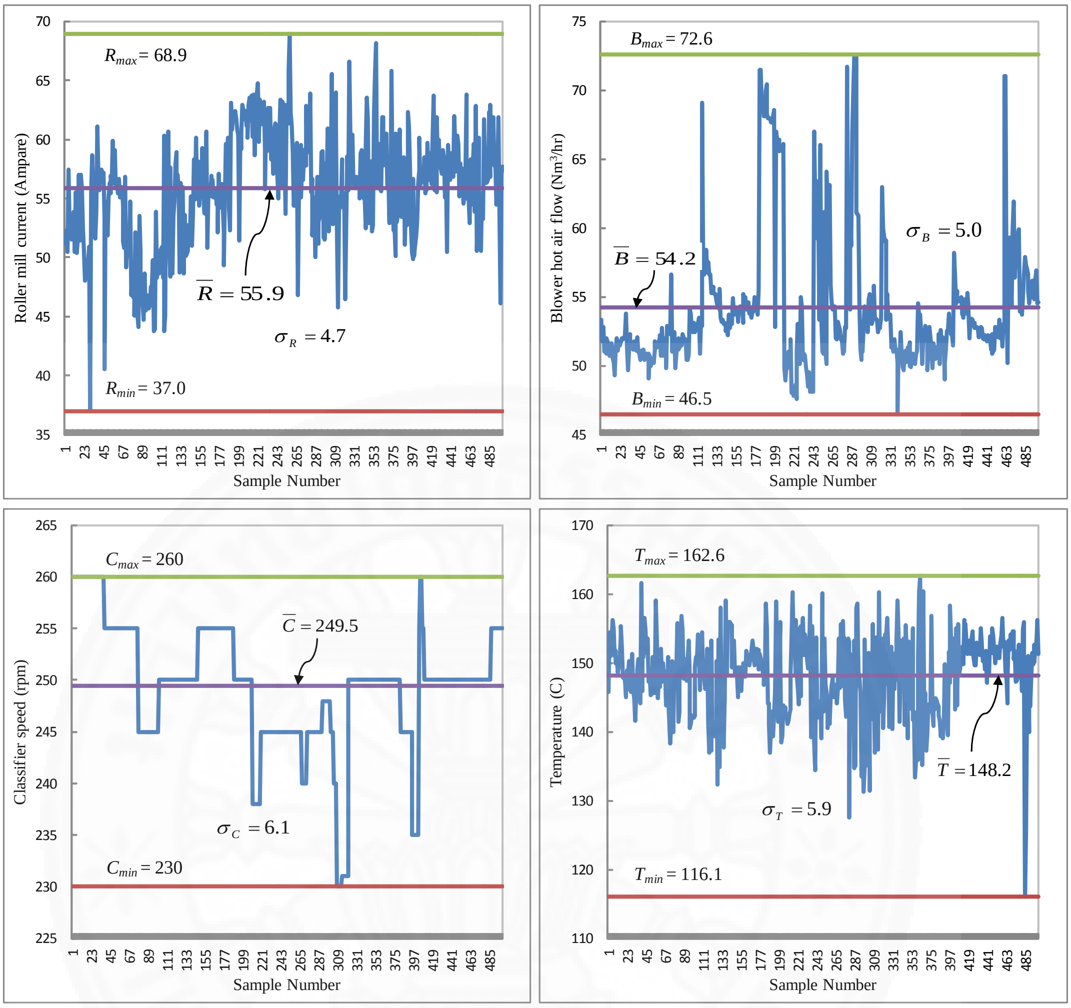



Fig. 3.1

All Input data of plaster production process collected from January – May 2015

In this study, five data sets of the plaster grinding process from January to May of year 2015 were investigated. Each month the process parameters consist of 100 data. Four input parameters, roller mill current ($R_i$), blower hot air flow current ($B_i$), classifier speed ($C_i$) and temperature ($T_i$) were applied as the input parameters of the purposed models. The output variable was combined water ($CW_i$). Then FIS model, ANFIS models and ANN model are proposed with these inputs and output data and compared the results to find out the best performance model for implementation in the plant.

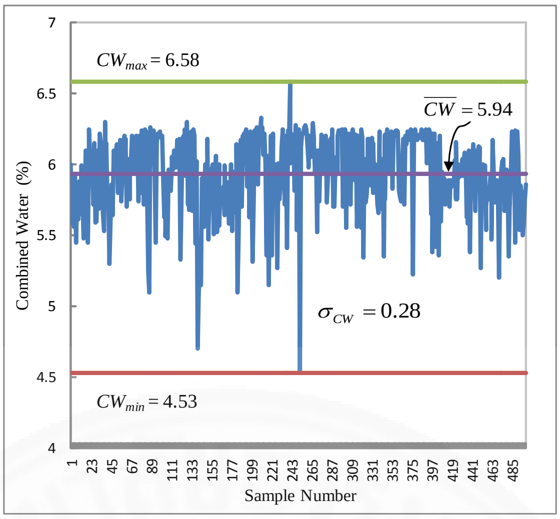



Fig. 3.2

Output data of plaster production process collected from January – May 2015

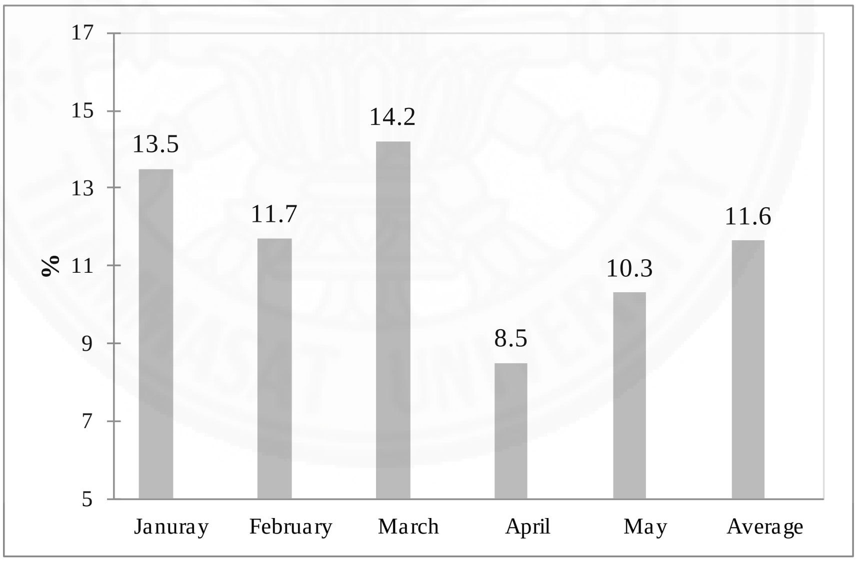



Figure 3.3

The percentage of defective products collected from January – May 2015

Although there are 4 inputs and 1 output, this kind of process control problem is complicated and very difficult to deal with normal operation and inexperience person. Generally, the plant operators need to be trained and supervised by experts, which control based on their knowledge experiences or historical data of the similar machines. If the plant does not use expertise and controls the process by trial and error with inexperience operators, the quality of plaster will inconsistency and result in a lot of defects of plasterboard production process. The AI methods are the beneficial methods for the plant to implement because of these are the proper methods such as FIS which utilizes expertise knowledge while ANN and ANFIS uses the process parameters as inputs and target data to train and test to get the output parameters. Furthermore, an application of AI to plaster process control has not been published. Then, this study purposed to present the applications of FIS, ANN and ANFIS to find out the best performance and suitable model for the plant.

### 3.1.1 FIS Application for process control

Fuzzy logic toolbox of MATLAB was implemented to the process control fuzzy inference system model to calculate combined water (*CW*). The flow chart of all parameters of the process control FIS model is illustrated in Fig. 3.4.

#### 3.1.1.1 Fuzzy inputs and fuzzy outputs

Fuzzy inputs are roller mill current ($R_i$), blower hot air flow current ($B_i$), classifier speed ($C_i$) and temperature ($T_i$). For systems with consequential dynamic variation in a short time frame, triangular or trapezoidal membership functions should be utilized (Bai and Wang 2006). Fuzzy inputs, represented by membership functions, $\mu_{R_i}, \mu_{B_i}, \mu_{C_i}$ and $\mu_{T_i}$, respectively, were settled relied on checking and validation of existing data. Fuzzy output is combined water ($CW_i$) which represented by membership functions, $\mu_{CW_i}$. The universe of discourse, memberships functions, linguistic values of each variable of fuzzy inputs and fuzzy output are displayed in Table 3.1. The inputs data for process control application are shown in Appendix A.

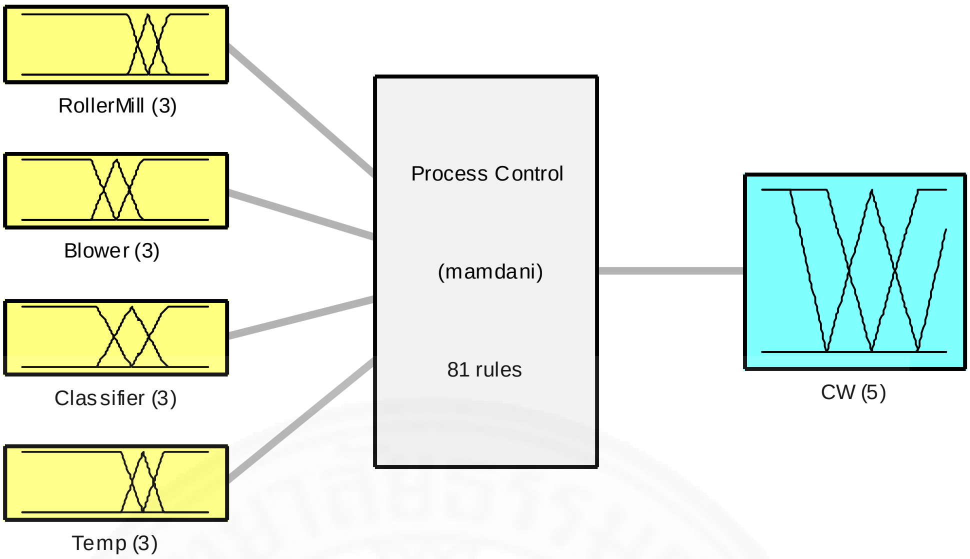



Fig. 3.4

The flow chart of the FIS model

Table 3.1

Description of fuzzy inputs and fuzzy output

| Fuzzy Parameters | Variables | Universe of discourse | Membership functions | Linguistic values* |
|---|---|---|---|---|
| Inputs | roller mill current ($\mu_R$) | [$R_{min}$, $R_{max}$] | $R_{min}$, $\bar{R}-\sigma_R$, $\bar{R}$, $\bar{R}+\sigma_R$, $R_{max}$ | L, M, H |
| | blower hot air flow current ($\mu_B$) | [$B_{min}$, $B_{max}$] | $B_{min}$, $\bar{B}-\sigma_B$, $\bar{B}$, $\bar{B}+\sigma_B$, $B_{max}$ | L, M, H |
| | classifier speed ($\mu_C$) | [$C_{min}$, $C_{max}$] | $C_{min}$, $\bar{c}-\sigma_C$, $\bar{C}$, $\bar{c}+\sigma_C$, $C_{max}$ | L, M, H |
| | temperature ($\mu_T$) | [$T_{min}$, $T_{max}$] | $T_{min}$, $\bar{T}-\sigma_T$, $\bar{T}$, $\bar{T}+\sigma_T$, $T_{max}$ | L, M, H |
| Output | Combined water ($\mu_{CW}$) | [$CW_{min}$, $CW_{max}$] | $CW_{min}$, $\overline{CW}-\sigma_{CW}$, $\overline{CW}$, $\overline{CW}+\sigma_{CW}$, $CW_{max}$ | VL, L, M, H, VH |

* VL = very low, L = low, M = medium, H = high, VH = very high

**3.1.1.2 Fuzzy rules**

The fuzzy rule is interpreted by an order of IF-THEN, according to algorithms describing what activity or output should be chosen with respect to the currently noticed information, which relates both input and feedback if a closed-loop control system is utilized. A set of fuzzy rules is developed by expert's experience or a human being's knowledge, which bases on each real condition. This IF-THEN rule is vastly utilized by the FIS to evaluate the degree to which the input data corresponds to the rule restriction. Since the outputs, combined water is fuzzy sets, a FIS of Mamdani type is selected for evaluating and aggregating the fuzzy rules. The IF-THEN rule can be mathematically described, as presented by Mandani and Assilian (1975), by Cartesian product of the fuzzy inputs, $x_1 \times x_2 \times x_3 \times x_4$. The relationship between roller mill current $x_1$, blower hot air flow current $x_2$, classifier speed $x_3$, temperature $x_4$, (IFs) and combined water $y_1$ (THEN) are described by 81 rules.

By utilizing the max-min compositional operation, the fuzzy reasoning of these rules creates fuzzy outputs. Fuzzy combined water ($\mu_{CW_i}(y_1)$) can be described as

$$\mu_{CW_i}(y_1) = (\mu^1_{R_i}(x_1) \wedge \mu^1_{B_i}(x_2) \wedge \mu^1_{C_i}(x_3) \wedge \mu^1_{T_i}(x_4) \vee \ldots$$

$$(\mu^n_{R_i}(x_1) \wedge \mu^n_{B_i}(x_2) \wedge \mu^n_{C_i}(x_3) \wedge \mu^n_{T_i}(x_4)), \quad (3.1)$$

where $\wedge$ is the minimum operation and $\vee$ is the maximum operation. $R_i$, $B_i$, $C_i$ , $T_i$ and $CW_i$ are fuzzy subsets represented by the according membership functions, i.e., $\mu_{R_i}, \mu_{B_i}, \mu_{C_i}, \mu_{T_i}, \mu_{CW_i}$.

Actually, the fuzzy output is also a linguistic variable, and this linguistic variable requires to be changed to the crisp variable during the defuzzification process. For this research, the central of gravity method is selected to change the fuzzy inference output into non-fuzzy values of combined water, $y_1^*$. Define rule number as $n$. The crisp values of combined water are computed as

$$y_1^* = \frac{\sum_{n=1}^{81} y_1(\mu^n_{CW_i}(y_1))}{\sum_{n=1}^{81} \mu^n_{CW_i}(y_1)} \quad , \quad \text{for } i = 1, 2, \ldots, n \quad (3.2)$$

MATLAB program source codes of FIS model for process control application is described in Appendix B. Example method to input data and get output data by using MATLAB is shown in Appendix C.

### 3.1.2 ANN for the process control problem

The two layer feed-forward with a back propagation learning algorithm was applied for the plaster process control model. The structure of ANN model is displayed in Fig. 3.5. The actual combined water data collected from the plant was utilized as the target data to define the ANN output. Similar to ANFIS, to determine with ANN, 80 data were chosen for training, 10 data for validation and 10 data for testing. The number of hidden neurons was identified as 5. The model was trained by applying Levenberg-Marguardt with back propagation algorithm. Example method to construct ANN model by using MATLAB is described in Appendix D.

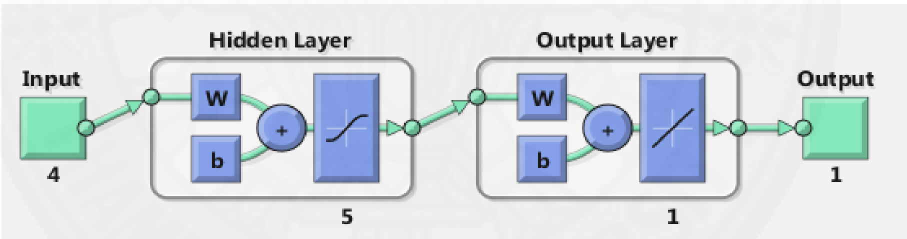



Fig. 3.5

The structure of ANN model

### 3.1.3 ANFIS for the process control problem

The structure of ANFIS model is illustrated in Fig. 3.6. The four input parameters were utilized as the training and testing data of ANFIS model. Each input consists of three membership functions (MFs). Then the 81 rules were utilized to normalize data and get the constant output for each data period.

An algorithm of the ANFIS models for the plaster process control is shown in Fig. 3.7 representing 3 phases. To determine with ANFIS, 80 data were chosen for training, 10 data for checking and 10 data for testing. All four inputs comprised of three MFs. The ANFIS models were generated by applying the various shapes of input MFs, trapezoidal and triangular (Trap), Gaussian (Gauss), and bell shape (Bell). To determine ANFIS outputs, a constant combined water (CW) was chosen. In MFs optimization, a hybrid of the back propagation gradient descent method and the least-squares method was applied to reproduce a specific training data set. MATLAB program source codes of ANFIS models for process control application are shown in Appendix B.

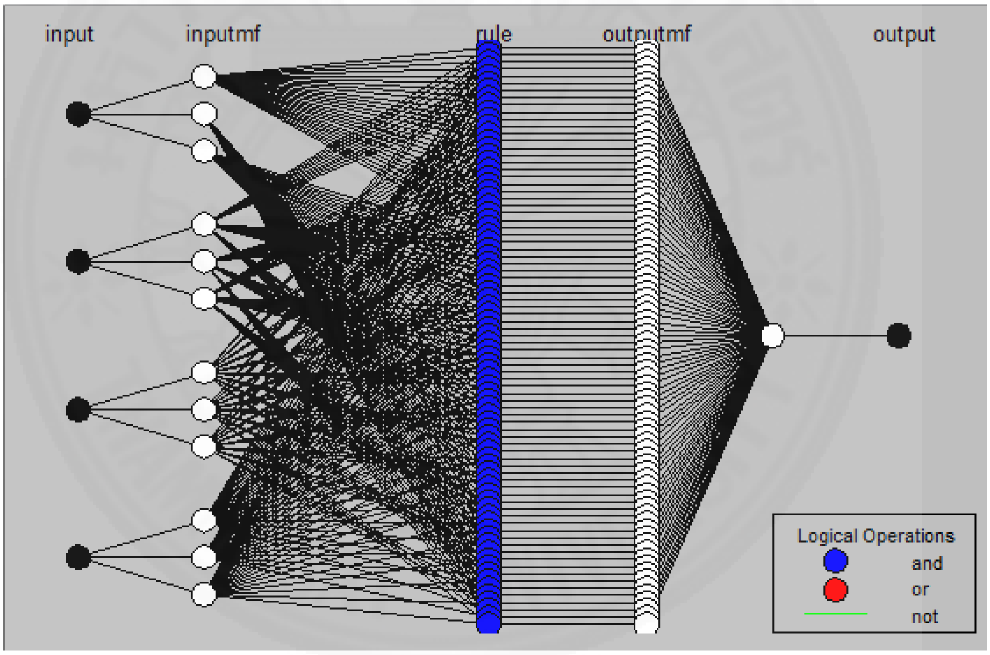



Fig. 3.6

The structure of ANFIS model for plaster process control

| **Phase 1: ANFIS Input selections** |
|---|
| Step 1: Determine MFs of inputs and outputs.<br>Step 2: Split data into three parts as training, testing and checking. |
| **Phase 2: Building and solving ANFIS Model** |
| Step 3: Load training, testing and checking data.<br>Step 4: Select grid partition method.<br>Step 5: Determine type of MFs, number of MFs, and type of output MFs.<br>Step 6: Choose MFs optimization method.<br>Step 7: Set number of epochs.<br>Step 8: Start train and get the training error. |
| **Phase 3: Evaluating and analysing results of ANFIS model** |
| Step 9 : Test the trained model with testing and checking data.<br>Step 10: View result and adjusted the generated rules or MFs.<br>Step 11: Calculate predicted accuracy. |

Fig. 3.7

Algorithms based on ANFIS for plaster process control

# CHAPTER 4
# RESEARCH METHODOLOGY FOR INVENTORY CONTROL APPLICATION

Inventory control is a critical function in manufacturing system, which can reduce a lot of cost for the factory. This chapter introduces the models of FIS, FIS with ANN, and FIS with ANFIS for inventory control for a furniture factory which has uncertain demand and supply. These models are compared and discussed in the following subsections.

## 4.1 Application for inventory control

The problem of inventory control has been investigated by using a case study of a furniture company in Thailand. The company is a made-to-order manufacturer that produces three main products which are door frames, stairs and plywood doors. Supply and demand of their products are both uncertain. The materials are imported from neighbouring countries and consist of timber woods, shorea obtusa woods, rubber woods and hopea woods. The main materials are timber woods. Availability of these materials is uncertain due to the quantity of timber woods based on environment, rainfall and sources of supply. Demand varies randomly but both demand and supply can be described by a normal distribution. Currently, a high inventory level is maintained to protect against shortage. The company guarantees to serve customers with more than 95% of service level efficiency. However, shortages still occur and the total inventory cost is high. These are serious problems for the company. So, FIS model, FIS+ANN model and FIS+ANFIS model were proposed to reduce the total inventory cost and inventory levels, and the results were compared with the conventional stochastic EOQ model. Fifteen data sets from the distribution of historical data were investigated. The distribution of historical demand was the normal with mean 2,452 units and standard deviation 776 units. Supply is also uncertain and can be described by the normal distribution with mean 6,487 units and standard deviation 3,921 units. From Fig. 4.1, it can be seen that the supply of material fluctuated extremely compared with demand and caused a shortage in some periods. Ordering cost, holding cost and shortage cost per unit per period of the case study factory were \$100, \$0.05 and \$59, respectively.

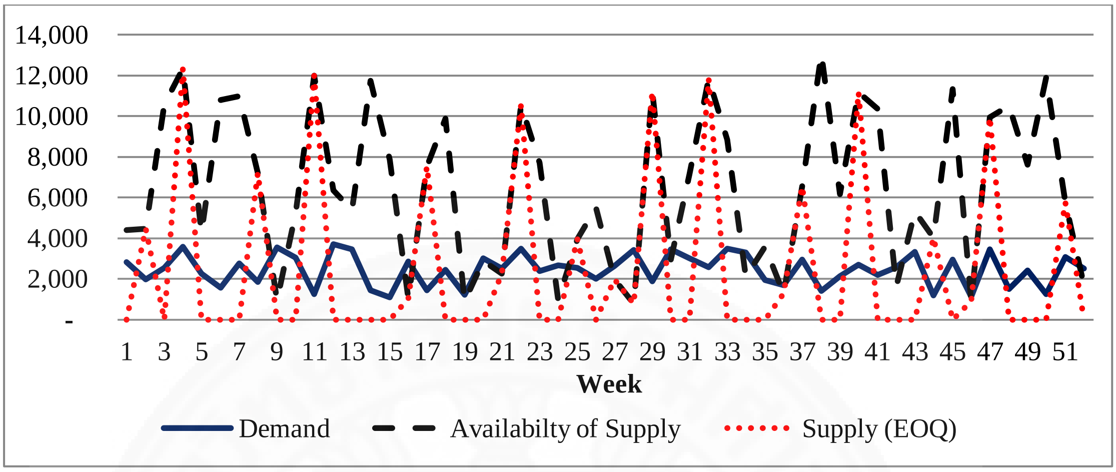
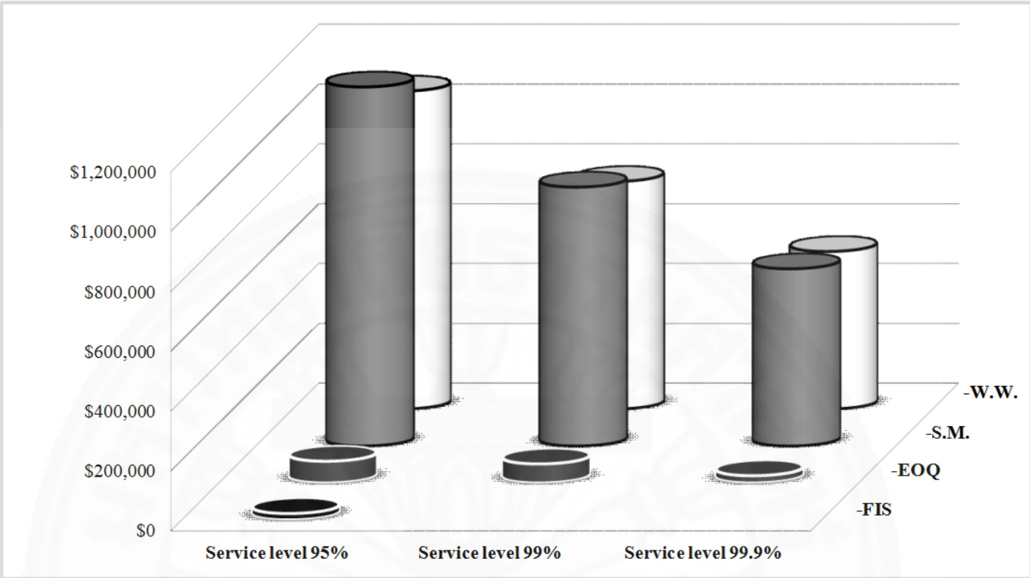



Fig 4.1

Fluctuation of demand and supply in 52 weeks

Although this problem consists of 2 inputs, uncertain demand and supply, and one output, order quantity, it is complicated to utilize the proper methodology for the practical inventory control system. Due to high fluctuation and uncertain of supply, the conventional deterministic model such as EOQ model which assume known parameters is not practical. The stochastic lot-sizing models such as Silver Meal (SM) and Wagner-Whitin (WW) can not cover and result in extremely high inventory costs. The dynamic stochastic lot-sizing models also complicated with difficult to implement. Furthermore, on basis of probability, stochastic models are efficient when input data is known exactly and available which is not practical with this kind of problem. Moreover, if the factory needs to serve their customers with high service level, they have to increase safety stocks or require enough holding inventory which will result in the problem of high inventory costs. The fuzzy logic method has been studied and applied to deal with uncertain demand and supply of the lot-sizing problem (Phruksaphanrat and Tanthatemee, 2013). A comparison of average total cost of conventional methods (SM, WW), stochastic EOQ method and FIS method is shown in Fig. 4.2. From Fig. 4.2, stochastic EOQ method has obtained better performance than conventional methods which insisted that conventional methods are not practical with this kind of problem. FIS method gave the best performance which represented the good method to deal with this problem. Anyway, good method does not mean the best method so the AI methods have studied and purposed in this dissertation to compare and insist for further improvement.




Note: FIS = Fuzzy Logic, EOQ = stochastic EOQ, S.M. = Silver Meal, W.W. = Wagner-Whitin

Fig. 4.2

A comparison of the average total costs of different models at service level 95, 99, 99.9% (Phruksaphanrat and Tanthatemee, 2013)

In this research, fuzzy logic toolbox of MATLAB was applied to the Fuzzy Inventory System (FIS) model to compute order quantity in any time period. The flow chart of all parameters of the inventory system model is illustrated in Fig. 4.3. The two fuzzy input variables are demand ($D_i$) and supply ($S_i$). The output variable is order quantity ($Q_i$), and is described by linguistic variables. Then the output is entered to the evaluation algorithm as shown in Fig. 4.4. The inputs data for inventory control application are tabulated in Appendix E. Example calculation of quantity and inventory cost is described in Appendix F.

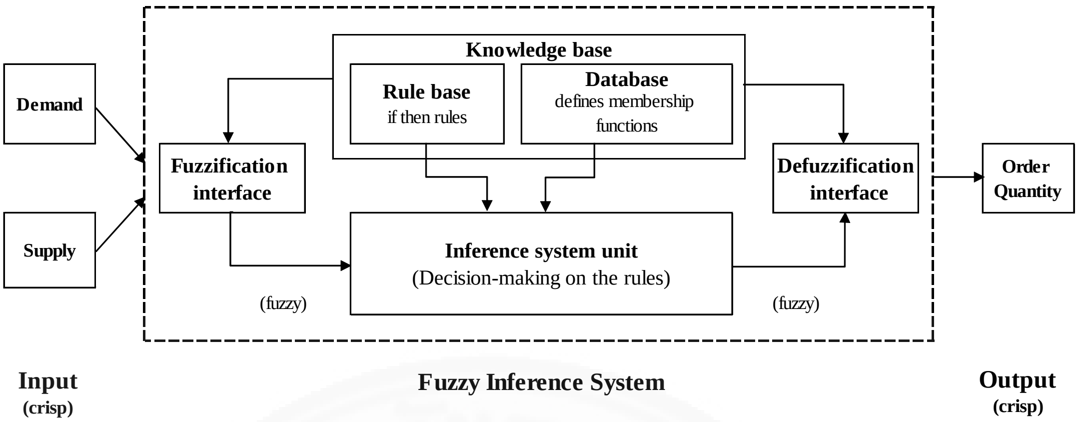



Fig. 4.3

A scheme of inference fuzzy inventory system

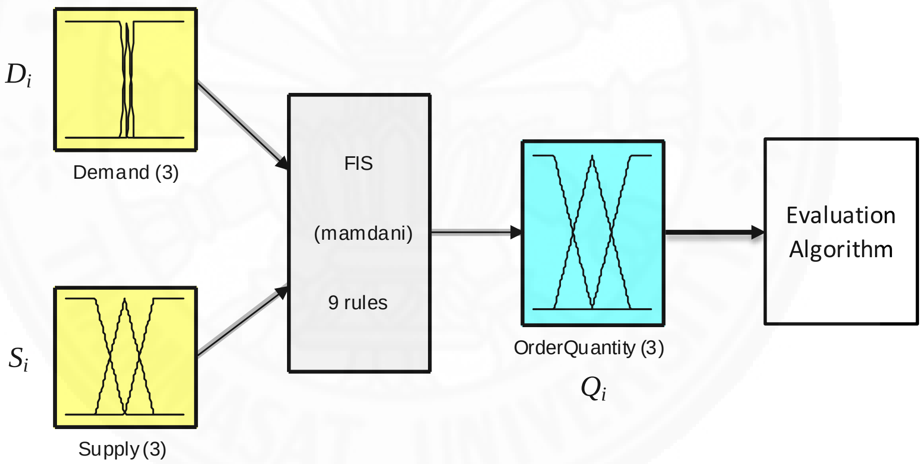
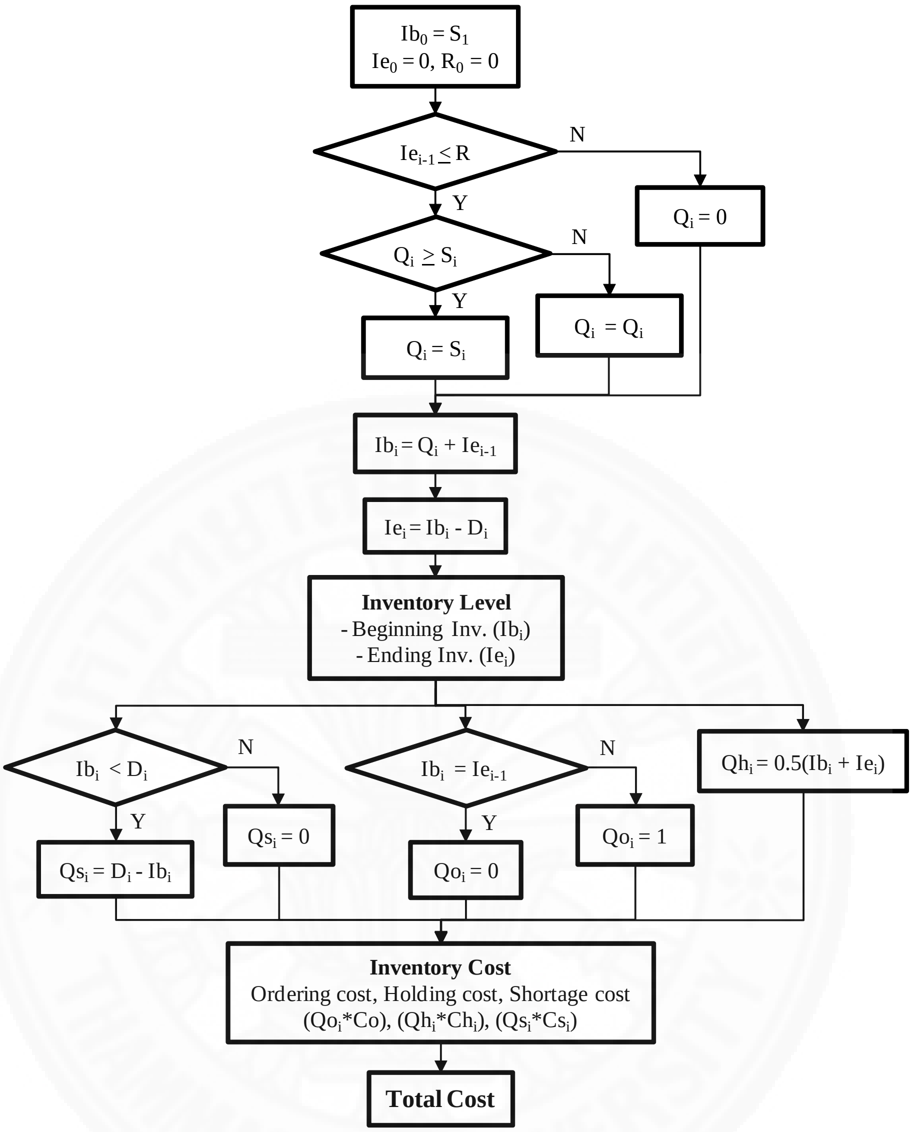



Fig. 4.4

The flow chart of the FIS model




**Note:**

$Ib_0$ = The beginning inventory at the end period of last year
$Ie_0$ = The ending inventory at the end period of last year
$R_0$ = Reorder point of last year
$R$ = Reorder point of this year
$Ib_i$ = The beginning inventory at period *i* of this year
$Ie_i$ = The ending inventory at period *i* of this year
$D_i$ = Demand at period *i* of this year
$S_i$ = Supply at period *i* of this year
$Q_i$ = Order quantity at period *i* of this year
$Qs_i$ = Shortage quantity at period *i* of this year
$Qo_i$ = Ordering quantity at period *i* of this year
$Qh_i$ = Holding quantity at period *i* of this year
$Cs_i$ = Shortage cost at period *i* of this year
Co = Ordering cost of this year
$Ch_i$ = Holding cost at period *i* of this year

Fig. 4.5

The evaluation algorithm of the inventory system model

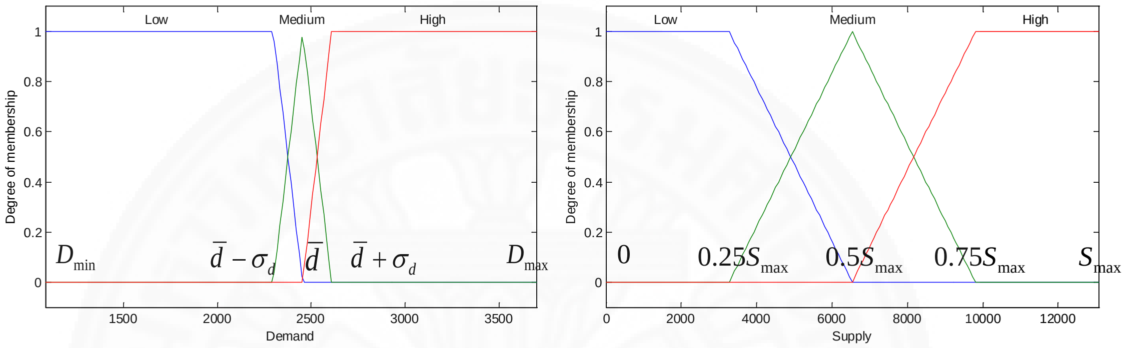
From Fig. 4.5, the inventory levels, which are a beginning inventory ($I_{b\,i}$) and the end inventory ($I_{e\,i}$) can be determined by output variable ($Q_i$) and reorder point ($R$). Then the inventory costs, which are ordering cost ($C_{o\,i}$), holding cost ($C_{h\,i}$) and shortage cost ($C_{s\,i}$) can be calculated by ordering quantity ($Q_{o\,i}$), holding quantity ($Q_{h\,i}$) and shortage quantity ($Q_{s\,i}$), respectively. The total cost per period is determined by the summation of the inventory costs. This fuzzy logic model then generates for the next period and follows this flow chart for each period ($i$ = 1, 2, 3, ..., $n$). Then the total inventory cost of the model is the summation of the total inventory costs of all periods.

### 4.1.1 FIS for the lot-sizing problem

#### 4.1.1.1 Fuzzy inputs

Fuzzy inputs are demand and supply. For systems with significant dynamic variation in a short period of time, triangular or trapezoidal membership functions should be utilized (Bai and Wang 2006). Fuzzy demand and fuzzy supply, represented by membership functions, $\mu_{D_i}$ and $\mu_{S_i}$, respectively, were determined based on observation and testing of historical data. Both of them are assumed to be represented by three linguistic values; low, medium, high.

The universe of discourse of demand input space was designed within the interval [$D_{min}$, $D_{max}$], where $D_{min}$ and $D_{max}$ are the minimum and maximum demand that had been ordered respectively. Demand membership functions rely on the parameters ($D_{min}$, $\overline{d}-\sigma_d$ , $\overline{d}$, $\overline{d}+\sigma_d$, $D_{max}$) as shown in Fig. 4.6(a). The parameters were designed depending on the characteristics of a normal distribution of uncertain demand of the factory. Supply was based on real data within the interval [0, $S_{max}$], where $S_{max}$ is the maximum supply from the current suppliers for determining planning horizon. Membership functions are shown in Fig. 4.6(b). The parameters (0, $0.25S_{max}$, $0.5S_{max}$, $0.75S_{max}$, $S_{max}$) were used for supply linguistic values according to the normal distribution.




(a) (b)

Fig. 4.6

Input membership functions (a) demand (b) supply

### 4.1.1.2 Fuzzy outputs

The fuzzy output, order quantity, is constructed and represented by membership functions, $\mu_{Q_i}$. Fuzzy order quantity is assumed to have three linguistic values; low, medium and high, represented by (0, $0.5S_{max}$-R, $0.5S_{max}$, $0.5S_{max}$+R, $S_{max}$) as shown in Fig. 4.7, with universe of discourse interval [0, $S_{max}$].

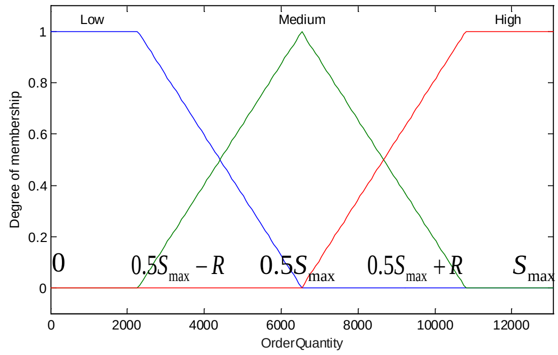



Fig. 4.7

Output membership functions, order quantity ( $\mu_{Q_i}$ )

#### 4.1.1.3 Fuzzy rules

The fuzzy rule is described by a sequence of IF-THEN, leading to algorithms representing what action or output should be taken in terms of the currently observed information, which includes both input and feedback if a closed-loop control system is applied. The guidance to design or build a set of fuzzy rules is based on a human being's knowledge or experience, which depends on each actual application. A fuzzy IF-THEN rule relates to a condition described using linguistic variables and fuzzy sets to an output or a conclusion. This IF-THEN rule is widely used by the fuzzy inference system to compute the degree to which the input data matches the condition of a rule. Since the output, order quantity is fuzzy sets, a Mamdani- type inference system is selected here for evaluating and aggregating the fuzzy rules. The relationship between demand $x_1$, supply $x_2$ (IFs) and order quantity $y_1$ (THEN) are represented by 9 rules as shown in Table 4.1.

By taking the max-min compositional operation, the fuzzy reasoning of these rules yields fuzzy outputs. Fuzzy order quantity ( $\mu_{Q_i}(y_1)$ ) can be expressed as

$$\mu_{Q_i}(y_1) = (\mu^1_{D_i}(x_1) \wedge \mu^1_{S_i}(x_2) \vee ...(\mu^n_{D_i}(x_1) \wedge \mu^n_{S_i}(x_2)), \qquad (4.1)$$

where $\wedge$ is the minimum operation and $\vee$ is the maximum operation. $D_i$, $S_i$ and $Q_i$

are fuzzy subsets defined by the corresponding membership functions, i.e., $\mu_{D_i}, \mu_{S_i}, \mu_{Q_i}$.

Table 4.1

The relationship of membership functions for each fuzzy rule

| Rule | $x_1$ | $x_2$ | $y_1$ |
|---|---|---|---|
| 1 | Low | Low | Medium |
| 2 | Low | Medium | Low |
| 3 | Low | High | Medium |
| 4 | Medium | Low | Low |
| 5 | Medium | Medium | Medium |
| 6 | Medium | High | High |
| 7 | High | Low | Medium |
| 8 | High | Medium | High |
| 9 | High | High | High |

Actually, the fuzzy output is still a linguistic variable, and this linguistic variable needs to be transformed to the crisp variable via the defuzzification process. For this case study, the center of gravity method is adopted to transform the fuzzy inference output into non-fuzzy values of order quantity, $y_1^*$. Define rule number as *n*. The crisp values of order quantity are calculated as

$$y_1^* = \frac{\sum_{n=1}^{9} y_1(\mu_{Q_i}^n(y_1))}{\sum_{n=1}^{9} \mu_{Q_i}^n(y_1)} \quad , \qquad \text{for } i = 1, 2, ..., n \tag{4.2}$$

MATLAB program source codes of FIS model for inventory control application are described in Appendix B. Example method to input data and get output data by using MATLAB is shown in Appendix C.

#### 4.1.1.4 Designing of input parameters

The proposed FIS model focuses on demand variation by adjusting the input membership function parameters with the designed universe of discourse of demand input space within the interval [$D_{min}$, $D_{max}$]. The demand membership function parameters are selected between ($D_{min}$, $\bar{d}-0.1\sigma_d$, $\bar{d}$, $\bar{d}+0.1\sigma_d$, $D_{max}$) to ($D_{min}$, $\bar{d}-1.7\sigma_d$, $\bar{d}$, $\bar{d}+1.7\sigma_d$, $D_{max}$). The first, the third and the fifth parameters are fixed because they are lower bound, midpoint and upper bound of the demand data. The second and the fourth parameters of the multiplier parameters of demand standard deviation ($\sigma_d$) are adjusted from 0.1 to 1.7. Fig. 4.8, compares the calculated average total costs of 15 data sets. The lowest average total cost is at ($D_{min}$, $\bar{d}-0.2\sigma_d$, $\bar{d}$, $\bar{d}+0.2\sigma_d$, $D_{max}$) or in abbreviated format denoted as ($\bar{d}\pm0.2\sigma_d$). Therefore in this case study, the recommended range of the membership function parameters for using the FIS model should be between the range of ($D_{min}$, $\bar{d}-0.2\sigma_d$, $\bar{d}$, $\bar{d}+0.2\sigma_d$, $D_{max}$) and ($D_{min}$, $\bar{d}-0.4\sigma_d$, $\bar{d}$, $\bar{d}+0.4\sigma_d$, $D_{max}$).

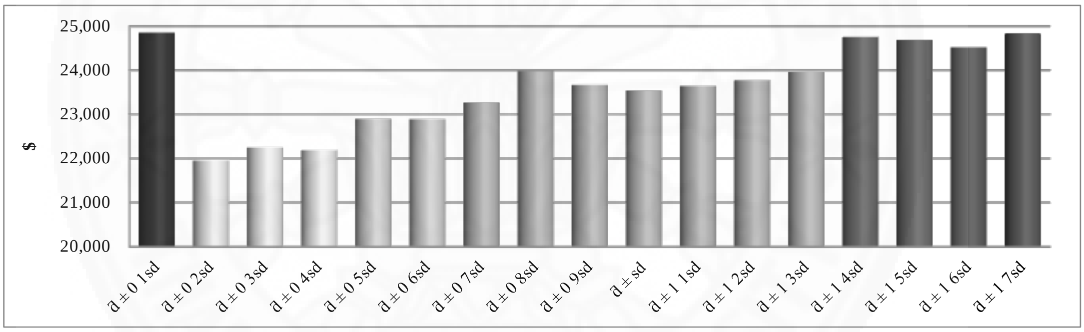



Fig. 4.8

The average total cost of 15 data sets of the proposed FIS model

ANN and ANFIS cannot directly apply to the inventory lot-sizing problem because the actual order quantities ($Q_i$) of inventory control system were high variation. In general, the order quantity consists of 2 types; order and not order. $Q_i$ is a specific value of order quantity if order whereas $Q_i$ is zero if not order. So for ANN and ANFIS models, the target data to train the inputs should not be very high variances which will result in training error of the models. In this study, the outputs from FIS model were selected to be the target data of ANN and ANFIS models.

#### 4.1.2. FIS with ANN for the lot-sizing problem

In this research, the two layer feed-forward with a back propagation learning algorithm was employed for the inventory model. The flow chart of FIS+ANN model is shown in Fig 4.9. The input data consisted of 52 demand and supply quantities. The output data from FIS model was used as the target data to define the ANN output. To determine with ANN, 42 data were selected for training, 5 data for validation and 5 data for testing. The number of hidden neurons was defined as 5. The model was trained by using Levenberg-Marguardt with back propagation algorithm. Then the output from ANN model was entered into the evaluation algorithm to calculate the total inventory cost of each time period. The total inventory cost of the model is the summation of inventory costs for all periods. Example method to construct ANN model by using MATLAB is described in Appendix D.

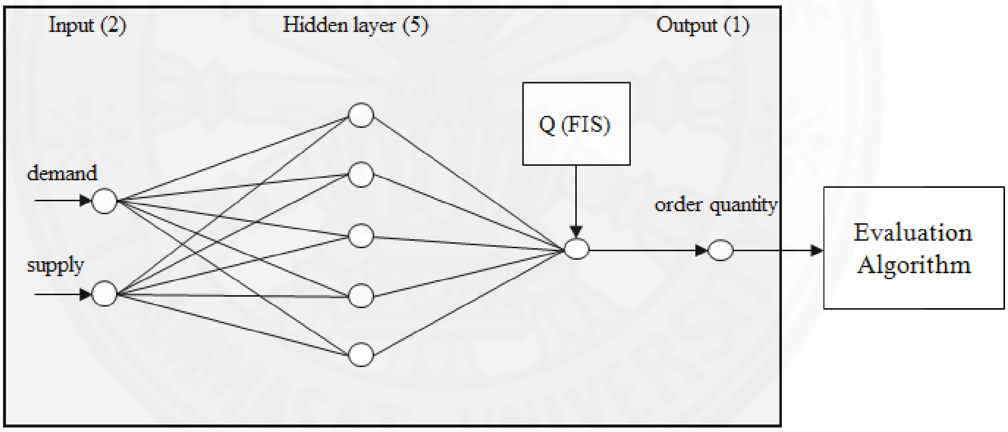



Fig. 4.9

The flow chart of FIS+ANN model

#### 4.1.3 FIS with ANFIS for the lot-sizing problem

The flow chart of FIS+ANFIS model is shown in Fig. 4.10 The output from FIS model was used as the training and testing data of ANFIS model. The result of ANFIS was entered to the evaluation algorithm to calculate the total inventory cost for each time period, then summed to give the inventory cost of the model.

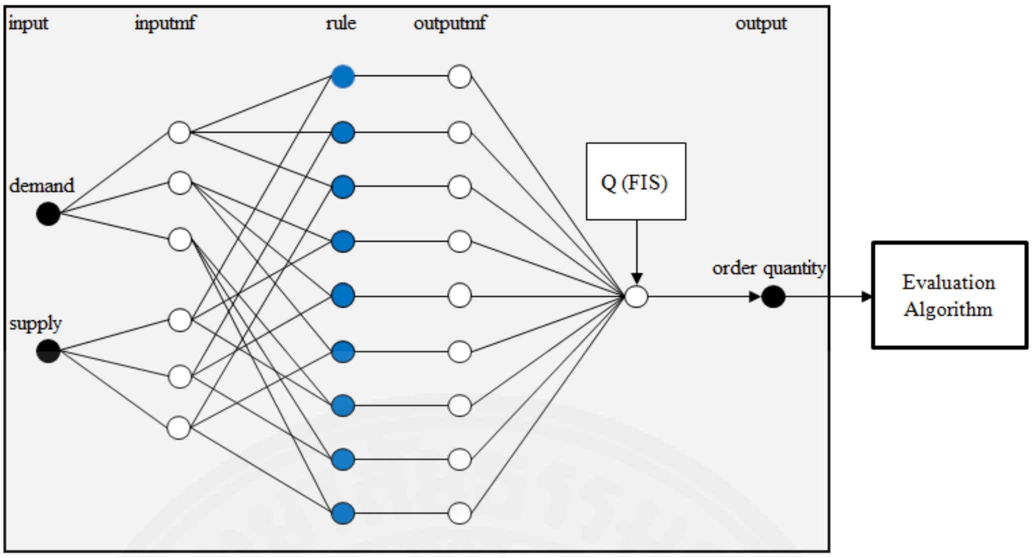



Fig. 4.10

The flow chart of FIS+ANFIS model

An algorithm of the model based on ANFIS for the inventory system is tabulated in Fig. 4.11 showing 3 phases. To determine with ANFIS, 42 data were selected for training, 5 data for checking or validation and 5 data for testing. Both demand and supply inputs consisted of three membership functions (MFs). The ANFIS models were developed by using the different shapes of input MFs, trapezoidal and triangular (Trap), Gaussian (Gauss), and bell shape (Bell). To determine ANFIS outputs, a constant order quantity (Q) was selected. In MFs optimization, a hybrid of the least-squares method and the back propagation gradient descent method was used to emulate a given training data set. A model ANFIS rules structure is shown in Fig. 4.12 in which there are two inputs for each of the 3 MFs. Then the 9 rules were applied to normalize data and get the constant output for each data period. MATLAB program source codes of ANFIS models for inventory control application are described in Appendix B.

**Phase 1: ANFIS Input selections**

Step 1: Determine MFs of inputs and outputs.
Step 2: Split data into two parts as training and testing.

**Phase 2: Building and solving ANFIS Model**

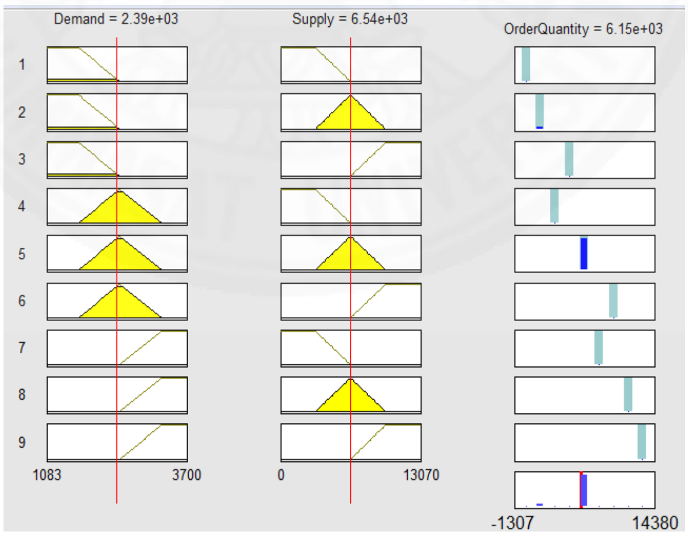
Step 3: Load training and testing data.
Step 4: Select grid partition method.
Step 5: Determine type of MFs, number of MFs, and type of output MFs.
Step 6: Choose MFs optimization method.
Step 7: Set number of epochs.
Step 8: Start train and get the training error.

**Phase 3: Evaluating and analysing results of ANFIS model**

Step 9 : Test the trained model with testing data.
Step 10: View result and adjusted the generated rules or MFs.
Step 11: Apply to fuzzy inventory system model and calculate total costs.
Step 12: Calculate predicted accuracy.

Fig. 4.11

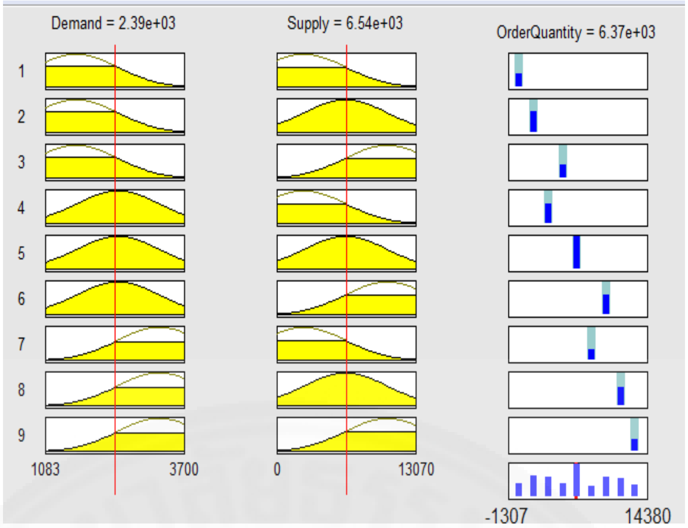
Algorithms based on ANFIS for inventory system



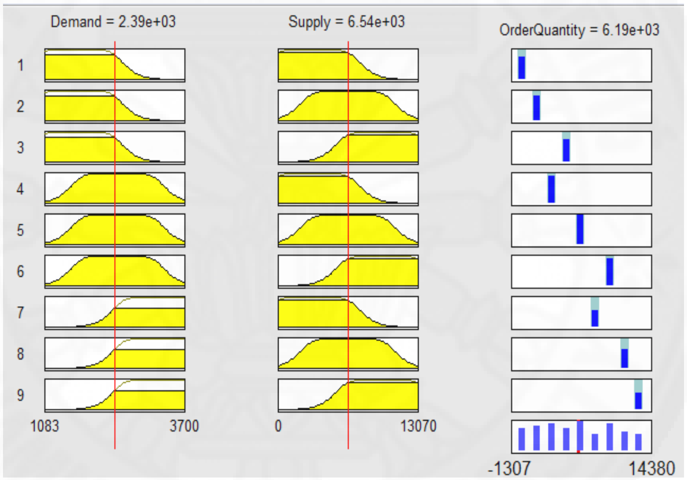

(a)

Fig. 4.12

ANFIS rules structure for each MF. (a) Trap




(b)




(c)

Fig. 4.12

ANFIS rules structure for each MF. (b) Gaussian (c) Bell

# CHAPTER 5
# RESULTS AND DISCUSSIONS

Validation of the proposed models with both inventory control and process control is needed. In this chapter, the k-fold cross validation is presented to evaluate the effectiveness of the proposed models. Then, the results of the proposed models, applied to process control and inventory control, which have uncertain inputs, are presented. These models are compared and discussed in the following subsections.

## 5.1 Results of process control application

### 5.1.1 K-fold cross validation of the proposed models

K-fold cross validation for process control application utilized the total 5 data sets. The training model was executed 5 times taking one group out at each time to check the model generality. Therefore, the candidate model is tested with all the data.

The range of input data and output data for each variable is shown in Table 5.1. All input data ranges from Table 5.1 were applied in each proposed model and then each model generated the output range accordingly. The average accuracy of the models was described by $R^2$, *RMSE* and *MAE* as tabulated in Table 5.2. The $R^2$ of ANFIS_Bell model represented the best performance, while ANN model showed the lowest performance. Anyway, all results insist to verify goodness of fit of the model performance.

Table 5.1

The range of input data and output data for each variable of the proposed models

| Parameters | | Minimum | Maximum | Average | SD |
|---|---|---|---|---|---|
| Input | *R* | 37.0 | 61.1 | 52.0 | 4.4 |
| | *B* | 49.1 | 56.6 | 51.4 | 1.0 |
| | *C* | 245.0 | 260.0 | 254.6 | 5.7 |
| | *T* | 138.3 | 161.6 | 148.8 | 4.4 |
| Output | *CW* | | | | |
| | FIS | 5.105 | 6.283 | 5.944 | 0.256 |
| | ANFIS_Trap | 5.104 | 6.286 | 5.918 | 0.262 |
| | ANFIS_Guass | 5.100 | 6.297 | 5.918 | 0.268 |
| | ANFIS_Bell | 5.097 | 6.283 | 5.918 | 0.265 |
| | ANN | 5.218 | 6.258 | 5.924 | 0.258 |

Note: SD = Standard deviation

Table 5.2

The K-fold cross validation results of each model

| | | FIS | ANFIS_Trap | ANFIS_Gauss | ANFIS_Bell | ANN |
|---|---|---|---|---|---|---|
| $R^2$ | K1 | 0.7374 | 0.7959 | 0.7989 | 0.7995 | 0.6686 |
| | K2 | 0.7025 | 0.7669 | 0.7753 | 0.7933 | 0.5700 |
| | K3 | 0.7294 | 0.7893 | 0.7929 | 0.8258 | 0.6875 |
| | K4 | 0.7744 | 0.8062 | 0.8042 | 0.8284 | 0.6917 |
| | K5 | 0.6654 | 0.7353 | 0.7455 | 0.7481 | 0.5780 |
| | Avg. | 0.7218 | 0.7787 | 0.7834 | **0.7990** | 0.6392 |
| *RMSE* | K1 | 0.1500 | 0.1315 | 0.1305 | 0.1303 | 0.1680 |
| | K2 | 0.1557 | 0.1368 | 0.1343 | 0.1288 | 0.1869 |
| | K3 | 0.1407 | 0.1241 | 0.1231 | 0.1129 | 0.1513 |
| | K4 | 0.1324 | 0.1207 | 0.1213 | 0.1135 | 0.1525 |
| | K5 | 0.1662 | 0.1461 | 0.1432 | 0.1425 | 0.1844 |
| | Avg. | 0.1490 | 0.1318 | 0.1305 | **0.1256** | 0.1686 |
| *MAE* | K1 | 0.0892 | 0.0832 | 0.0833 | 0.0842 | 0.1147 |
| | K2 | 0.0927 | 0.0833 | 0.0828 | 0.0766 | 0.1227 |
| | K3 | 0.0834 | 0.0770 | 0.0720 | 0.0679 | 0.1003 |
| | K4 | 0.0863 | 0.0757 | 0.0778 | 0.0743 | 0.1074 |
| | K5 | 0.1026 | 0.0937 | 0.0955 | 0.0936 | 0.1289 |
| | Avg. | 0.0908 | 0.0826 | 0.0823 | **0.0793** | 0.1148 |

Best performance results are highlighted in bold

### 5.1.2 Results of the proposed models application to process control

The fuzzy process control models of the plaster manufacturing system have been modelled systematically as well as with ANFIS and ANN approaches. The results acquired from the generated models presented that the ANFIS models outperformed FIS model and ANN model. The comparison of statistical values of 5 data sets for each model is displayed in Table 5.3.

The result of prediction efficiency represented that ANFIS_Bell model is outstanding, followed by ANFIS_Gauss model, ANFIS_Trap model, FIS model and ANN model, respectively. The training and checking curves of all proposed ANFIS models of data set 1 for process control application are shown in Fig. 5.1. Plot of each membership function of data set 1 for process control application are shown in Fig. 5.2.

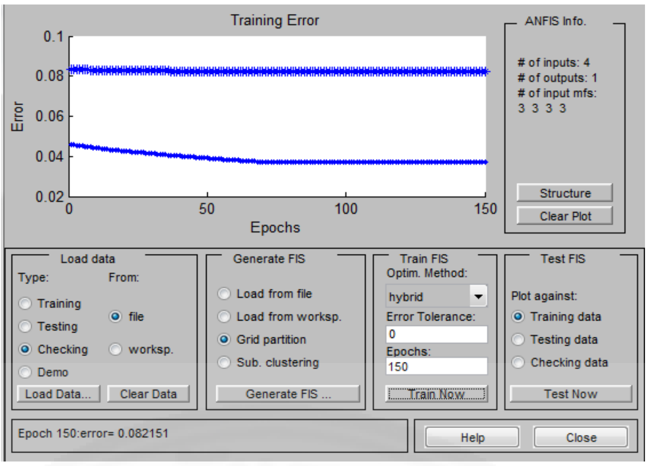
Concerning to prediction efficiency, FIS+ANFIS_Bell model and FIS+ANFIS_Gauss model were suitable to utilize. Then, all models were implemented in the case study plant.

Table 5.3

The comparison of statistical values of 5 data sets for each model

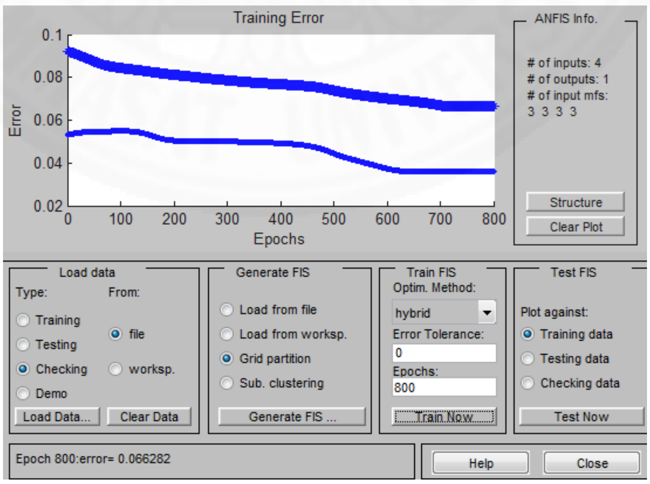
| | Data set | FIS | ANFIS_Trap | ANFIS_Gauss | ANFIS_Bell | ANN |
|---|---|---|---|---|---|---|
| *$R^2$* | D1 | 0.8045 | 0.9095 | 0.9558 | 0.9411 | 0.8168 |
| | D2 | 0.6939 | 0.8757 | 0.9275 | 0.9512 | 0.6577 |
| | D3 | 0.5502 | 0.6881 | 0.8931 | 0.9317 | 0.6192 |
| | D4 | 0.9898 | 0.9881 | 0.9934 | 0.9933 | 0.8225 |
| | D5 | 0.5768 | 0.8196 | 0.8496 | 0.8695 | 0.5279 |
| | Avg. | 0.7230 | 0.8562 | 0.9239 | **0.9374** | 0.6888 |
| *RMSE* | D1 | 0.1211 | 0.0821 | 0.0574 | 0.0663 | 0.1173 |
| | D2 | 0.1804 | 0.1075 | 0.0821 | 0.0674 | 0.1792 |
| | D3 | 0.2013 | 0.1645 | 0.0963 | 0.0769 | 0.1868 |
| | D4 | 0.0251 | 0.0266 | 0.0198 | 0.0199 | 0.1029 |
| | D5 | 0.1476 | 0.0942 | 0.0860 | 0.0801 | 0.1527 |
| | Avg. | 0.1351 | 0.0950 | 0.0683 | **0.0621** | 0.1478 |
| *MAE* | D1 | 0.0698 | 0.0524 | 0.0309 | 0.0429 | 0.0781 |
| | D2 | 0.1083 | 0.0706 | 0.0569 | 0.0446 | 0.1346 |
| | D3 | 0.0950 | 0.0913 | 0.0626 | 0.0481 | 0.1303 |
| | D4 | 0.0253 | 0.0198 | 0.0128 | 0.0126 | 0.0705 |
| | D5 | 0.0825 | 0.0572 | 0.0512 | 0.0468 | 0.1027 |
| | Avg. | 0.0762 | 0.0582 | 0.0429 | **0.0390** | 0.1032 |

Best performance results are highlighted in bold




(a)


(b)

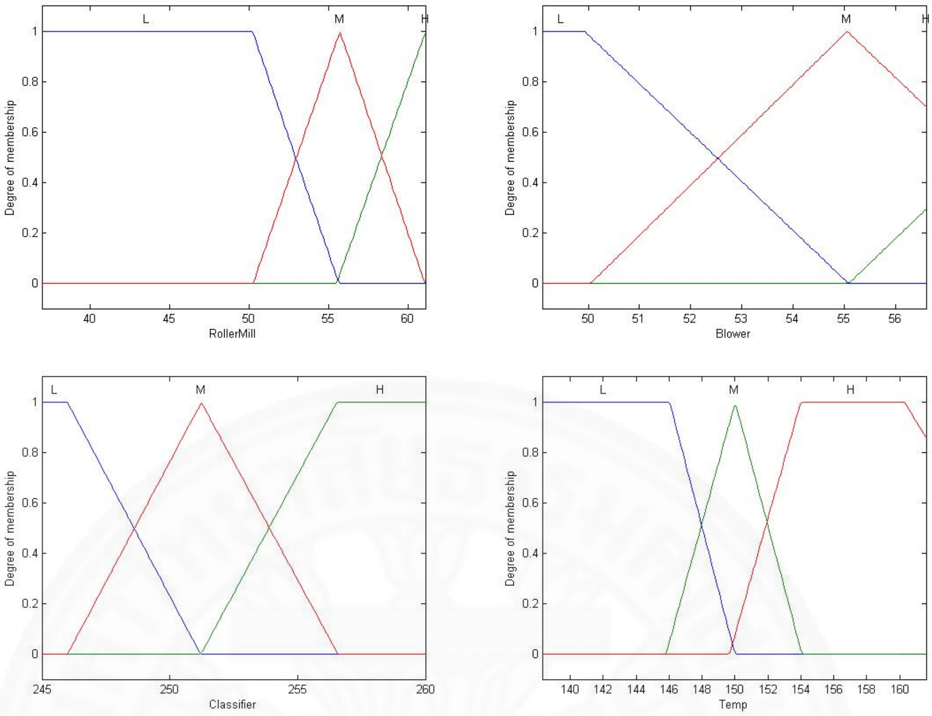



(c)

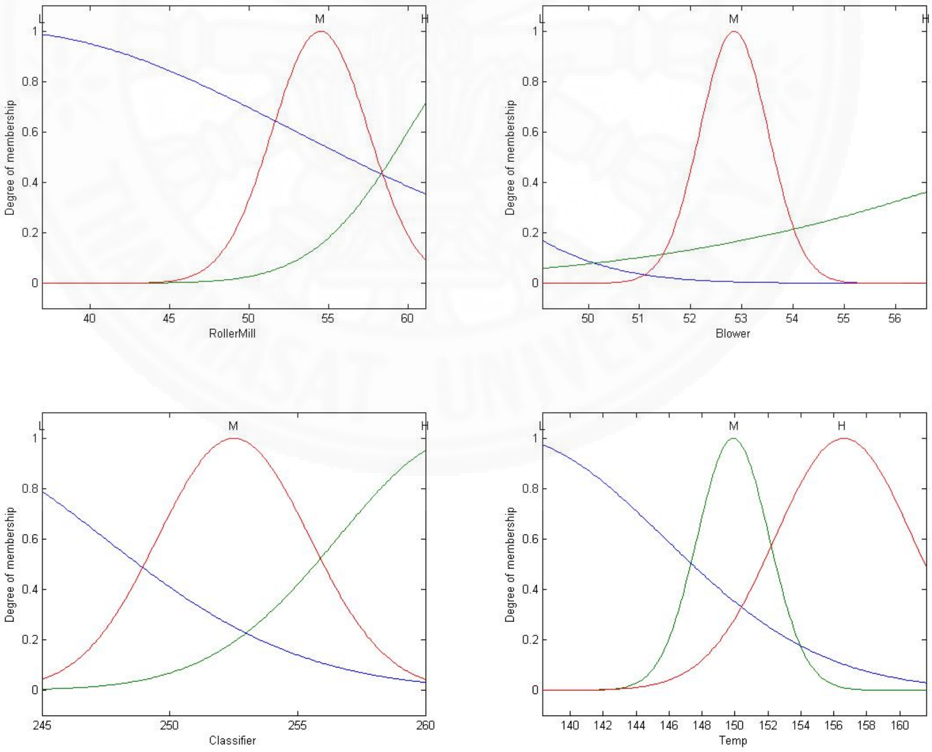
Fig. 5.1

Training and checking curves of data set 1 for process control application

(a) ANFIS_Trap model (b) ANFIS_Gauss model (c) ANFIS_Bell model




(a)

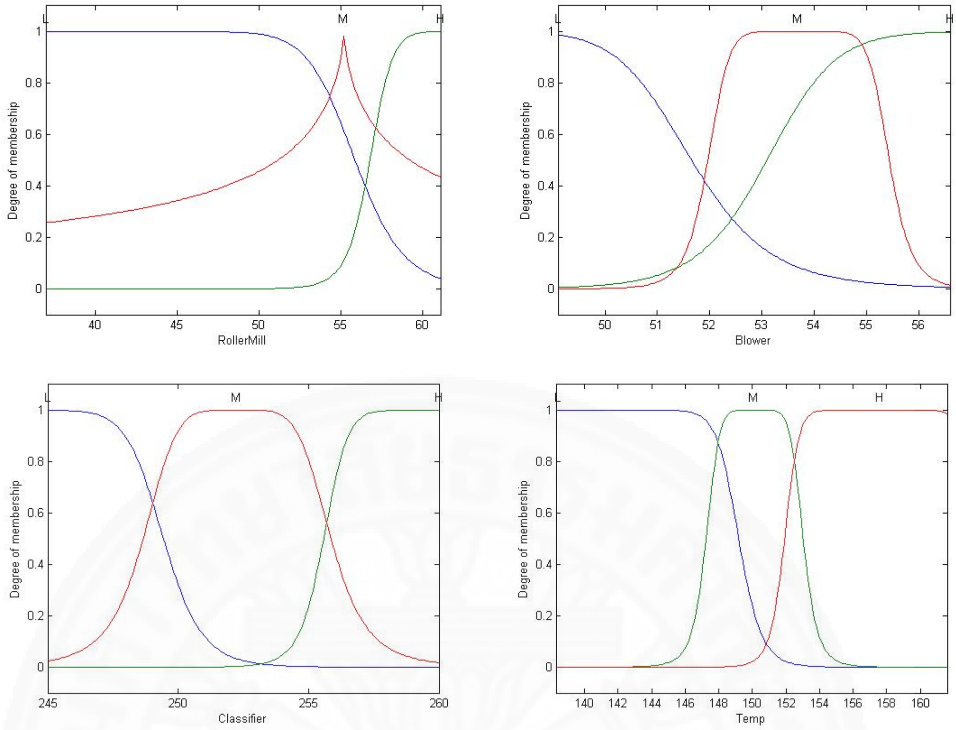



(b)

Fig. 5.2

Plot of each MF of data set 1 for process control application

(a) ANFIS_Trap model (b) ANFIS_Gauss model




(c)

Fig. 5.2

Plot of each MF of data set 1 for process control application

(c) ANFIS_Bell model

The comparison of defects of each model with average defects before implementation is shown in Fig. 5.3. From Fig. 5.3, all models performed well with the defect rate compared to the average defect rate of the previous 5 months. The ANFIS_Bell model achieved the lowest defect rate which reduced 5.2% (from 11.6% to 6.4%) compared to average defects before implementation, followed by ANFIS_Gauss model, ANFIS_Trap model, FIS model and ANN model, respectively. The reduction of the defects was also insisted the beneficial of the proposed model when applying to real process control application of the plant.

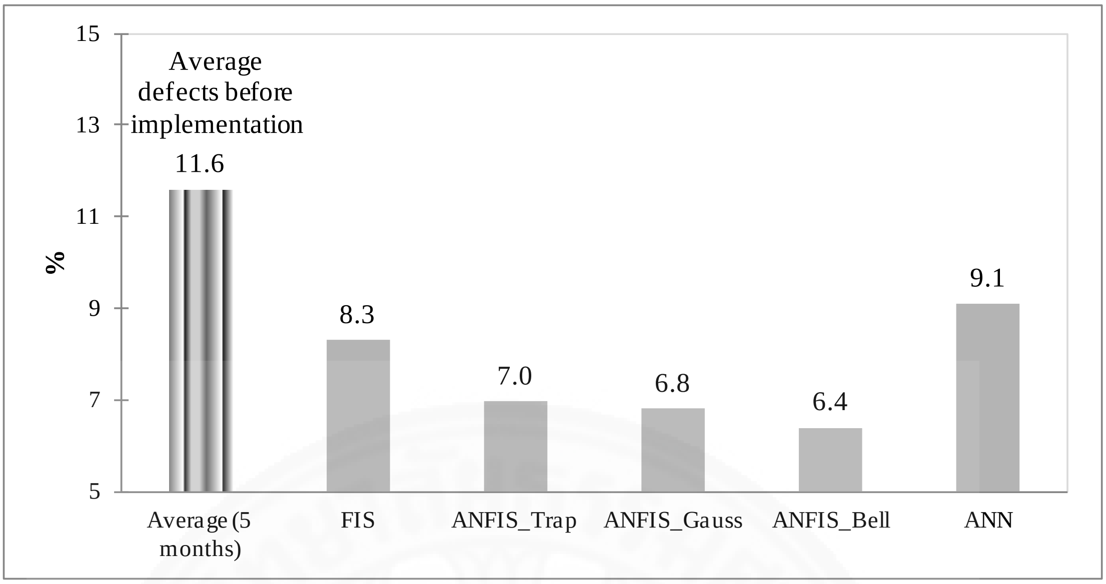



Fig. 5.3

The comparison of defects of each model with average defects before implementation

## 5.2 Results of inventory control application

### 5.2.1 K-fold cross validation of the proposed models

In this research, the total 15 data sets were separated into 5 even groups, and then the modelling training was implemented 5 times taking one group out at each time to check the model generality. By this method, the candidate model is examined by the all data.

The average accuracy of the models was represented by $R^2$, *RMSE* and *MAE* as shown in Table 5.4. The $R^2$ of all models has achieved greater than 0.9, which verify goodness of the model performance.

Table 5.4

The K-fold cross validation results of each model

| | | ANFIS_Trap | ANFIS_Gauss | ANFIS_Bell | ANN |
|---|---|---|---|---|---|
| $R^2$ | K1 | 0.9774 | 0.9671 | 0.9110 | 0.9875 |
| | K2 | 0.9695 | 0.8495 | 0.9157 | 0.9700 |
| | K3 | 0.9739 | 0.9680 | 0.9153 | 0.9717 |
| | K4 | 0.9889 | 0.9743 | 0.9115 | 0.9719 |
| | K5 | 0.9784 | 0.9710 | 0.9181 | 0.9735 |
| | Avg. | **0.9776** | 0.9460 | 0.9143 | 0.9749 |
| *RMSE* | K1 | 367 | 443 | 727 | 360 |
| | K2 | 422 | 945 | 702 | 374 |
| | K3 | 353 | 390 | 635 | 362 |
| | K4 | 240 | 366 | 679 | 410 |
| | K5 | 314 | 363 | 609 | 382 |
| | Avg. | **339** | 502 | 670 | 377 |
| *MAE* | K1 | 202 | 324 | 555 | 198 |
| | K2 | 228 | 460 | 513 | 220 |
| | K3 | 162 | 272 | 465 | 169 |
| | K4 | 134 | 253 | 469 | 280 |
| | K5 | 167 | 260 | 450 | 187 |
| | Avg. | **179** | 314 | 491 | 211 |

Best performance results are highlighted in bold

### 5.2.2 Results of the proposed models application to inventory control

The inventory models of both fuzzy demand and supply have been modelled analytically as well as with ANN and ANFIS approaches. The results derived from the developed models show that the FIS+ANFIS models outperformed FIS+ANN model. The comparison of statistical values of 15 data sets for each model is shown in Table 5.5. This comparison is based on FIS model that had been verified for its effectiveness with the conventional models; stochastic EOQ model, Silver Meal model and Wagner Whitin model.

The result of prediction performance showed that FIS+ANFIS_Trap model is outstanding, followed by FIS+AIS_Gauss model, FIS+ANFIS_Bell model and FIS+ANN model, respectively. For FIS+ANFIS models, the results of running times (epochs) showed that the lowest running time was FIS+ANFIS_Bell model, followed by FIS+ANFIS_Gauss model and FIS+ANFIS_Trap model, respectively.

Table 5.5

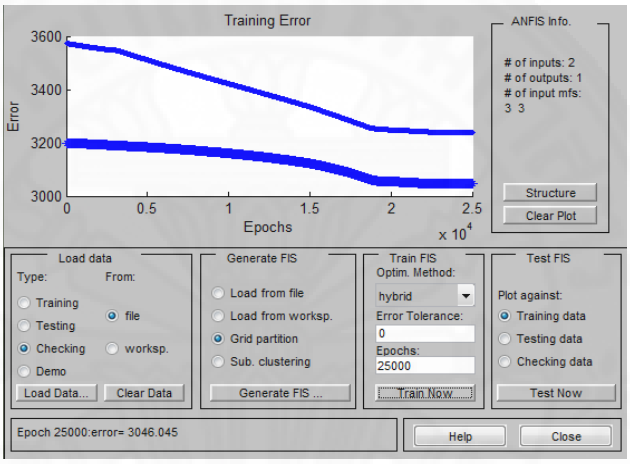
The comparison of statistical values of 15 data sets for each model

| Q | Data set | FIS+ANN | FIS+ANFIS_Trap | FIS+ANFIS_Gauss | FIS+ANFIS_Bell |
|---|---|---|---|---|---|
| **$R^2$** | D1 | 0.855 | 0.981 | 0.944 | 0.957 |
| | D2 | 0.768 | 0.993 | 0.992 | 0.918 |
| | D3 | 0.939 | 0.997 | 0.942 | 0.800 |
| | D4 | 0.950 | 0.999 | 0.921 | 0.944 |
| | D5 | 0.563 | 0.937 | 0.952 | 0.929 |
| | D6 | 0.819 | 0.969 | 0.968 | 0.963 |
| | D7 | 0.898 | 0.976 | 0.964 | 0.962 |
| | D8 | 0.766 | 0.966 | 0.945 | 0.949 |
| | D9 | 0.988 | 0.976 | 0.847 | 0.778 |
| | D10 | 0.925 | 0.958 | 0.930 | 0.854 |
| | D11 | 0.887 | 0.995 | 0.995 | 0.955 |
| | D12 | 0.852 | 0.994 | 0.975 | 0.837 |
| | D13 | 0.933 | 0.992 | 0.987 | 0.876 |
| | D14 | 0.925 | 0.974 | 0.976 | 0.887 |
| | D15 | 0.848 | 0.966 | 0.936 | 0.923 |
| | Avg. | 0.861 | **0.978** | 0.952 | 0.902 |
| **RMSE** | D1 | 852 | 306 | 531 | 464 |
| | D2 | 1,284 | 222 | 232 | 758 |
| | D3 | 582 | 137 | 570 | 1,087 |
| | D4 | 579 | 94 | 728 | 609 |
| | D5 | 1,497 | 562 | 492 | 599 |
| | D6 | 1,022 | 419 | 425 | 461 |
| | D7 | 639 | 308 | 375 | 389 |
| | D8 | 1,101 | 418 | 534 | 519 |
| | D9 | 260 | 363 | 977 | 1,115 |
| | D10 | 655 | 485 | 628 | 908 |
| | D11 | 749 | 151 | 151 | 470 |
| | D12 | 935 | 182 | 371 | 1,015 |
| | D13 | 552 | 189 | 249 | 753 |
| | D14 | 541 | 316 | 306 | 662 |
| | D15 | 884 | 419 | 572 | 630 |
| | Avg. | 809 | **305** | 476 | 696 |
| **MAE** | D1 | 625 | 146 | 332 | 308 |
| | D2 | 978 | 60 | 155 | 567 |
| | D3 | 396 | 52 | 417 | 730 |
| | D4 | 390 | 61 | 592 | 412 |
| | D5 | 1,015 | 308 | 321 | 443 |
| | D6 | 994 | 235 | 232 | 281 |
| | D7 | 379 | 76 | 146 | 259 |
| | D8 | 780 | 236 | 418 | 369 |
| | D9 | 183 | 92 | 345 | 894 |
| | D10 | 471 | 280 | 490 | 670 |
| | D11 | 518 | 72 | 101 | 332 |
| | D12 | 755 | 108 | 191 | 530 |
| | D13 | 397 | 111 | 191 | 586 |
| | D14 | 408 | 144 | 161 | 441 |
| | D15 | 619 | 214 | 450 | 498 |
| | Avg. | 594 | **146** | 303 | 488 |

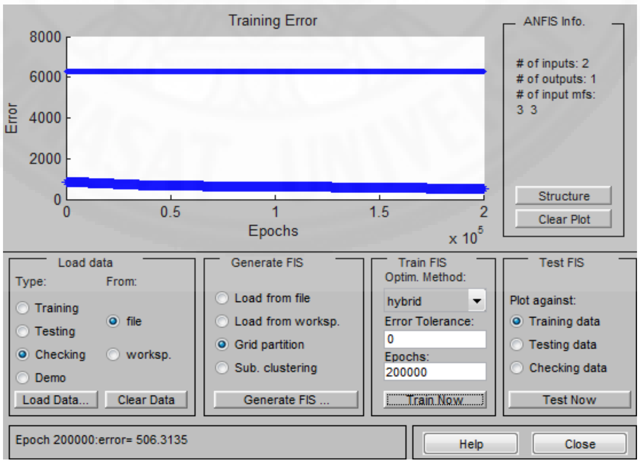
Note: Avg. is average

The training and checking curves of all proposed FIS+ANFIS models of data set 1 for inventory control application are shown in Fig. 5.4. Plot of each membership function of data set 1 for inventory control application is shown in Fig. 5.5.

For implementation based on prediction performance, FIS+ANFIS_Trap model and FIS+ANFIS_Gauss model were suitable to use. However, based on running times, FIS+ANFIS_Bell model and FIS+ANFIS_Trap model were appropriate for the decision maker.




(a)

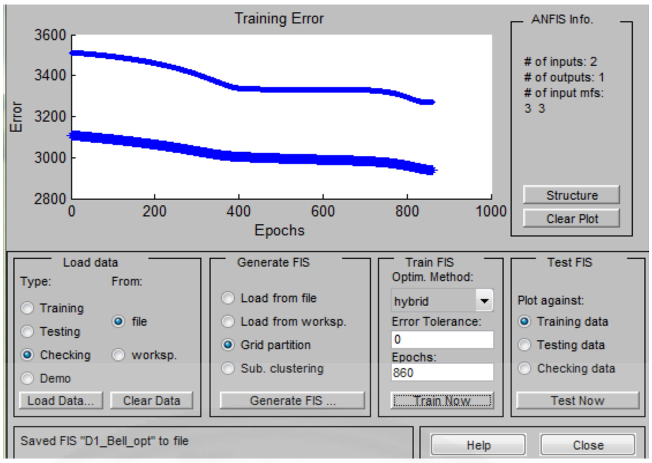



(b)

Fig. 5.4

Training and checking curves of data set 1 for inventory control application

(a) FIS+ANFIS_Trap model (b) FIS+ANFIS_Gauss model

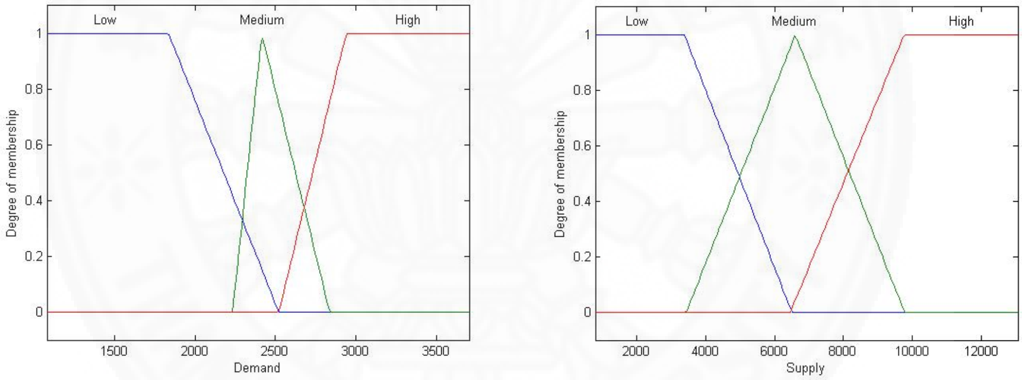



(c)

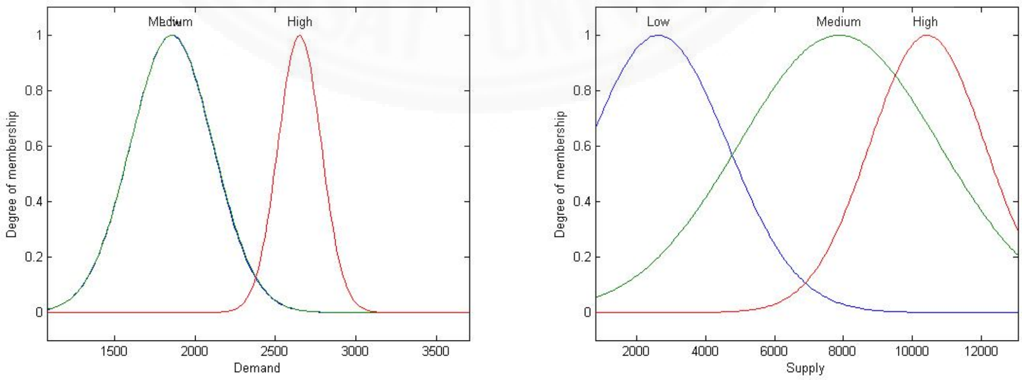
Fig. 5.4

Training and checking curves of data set 1 for inventory control application

(c) FIS+ANFIS_Bell model




(a)

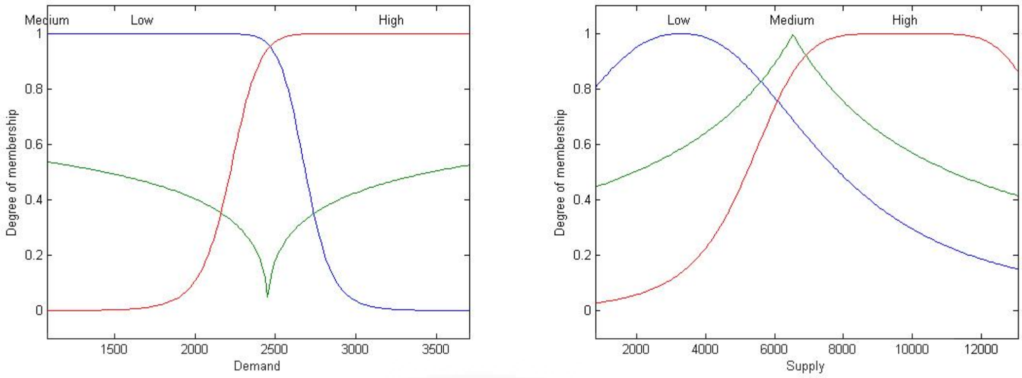



(b)

Fig. 5.5

Plot of each MF of data set 1 for inventory control application

(a) FIS+ANFIS_Trap model (b) FIS+ANFIS_Gauss model




(c)

Fig. 5.5

Plot of each MF of data set 1 for inventory control application

(c) FIS+ANFIS_Bell model

The results of each proposed model after entering the predicted values to the evaluation algorithm and calculating the total inventory costs is shown in Table 5.6. The ordering costs increased whereas, the larger holding costs decreased for all models when compared with stochastic EOQ model.

The average total inventory cost of all data sets and cost saving of all models compared to stochastic EOQ model is shown in Table 5.7. All models performed well with total inventory cost saving. The FIS+ANFIS_Gauss model achieved the largest cost saving by more than 75% compared to stochastic EOQ model, followed by FIS+ANFIS_Bell model, FIS model, FIS+ANFIS_Trap model and FIS+ANN model, respectively. Although FIS+ANFIS_Trap model outperformed stochastic EOQ prediction when applied as the inventory model it represented the lowest cost saving, because some predicted values were affected by shortages which caused the shortage cost to be more than 30% of the total cost.

Table 5.6

The total inventory cost of 15 data sets for each model

| Inventory cost | Data set | Stochastic EOQ | FIS | FIS+ANN | FIS+ANFIS_Trap | FIS+ANFIS_Gauss | FIS+ANFIS_Bell |
|---|---|---|---|---|---|---|---|
| **Holding cost ($)** | D1 | 16,093 | 12,775 | 14,906 | 12,806 | 14,852 | 14,578 |
| | D2 | 15,944 | 13,975 | 15,207 | 14,191 | 13,615 | 13,923 |
| | D3 | 16,413 | 15,585 | 13,581 | 14,094 | 13,601 | 14,755 |
| | D4 | 18,043 | 13,679 | 15,255 | 13,991 | 14,609 | 15,561 |
| | D5 | 16,617 | 12,398 | 13,488 | 12,943 | 11,895 | 13,458 |
| | D6 | 18,314 | 15,864 | 13,708 | 15,433 | 16,430 | 14,926 |
| | D7 | 17,153 | 14,676 | 15,174 | 14,996 | 14,955 | 15,467 |
| | D8 | 17,269 | 13,977 | 14,174 | 13,589 | 14,086 | 14,559 |
| | D9 | 16,710 | 14,248 | 14,839 | 14,182 | 14,627 | 14,447 |
| | D10 | 15,720 | 14,587 | 13,974 | 14,910 | 13,813 | 14,408 |
| | D11 | 16,275 | 14,814 | 13,164 | 14,903 | 14,854 | 14,553 |
| | D12 | 16,272 | 14,071 | 14,894 | 14,088 | 13,989 | 13,737 |
| | D13 | 16,289 | 13,771 | 15,242 | 13,781 | 13,922 | 15,227 |
| | D14 | 16,441 | 13,093 | 14,299 | 13,139 | 13,062 | 13,124 |
| | D15 | 16,434 | 14,761 | 14,778 | 15,658 | 15,879 | 15,880 |
| | Avg. | 16,666 | **14,152** | 14,445 | 14,180 | 14,279 | 14,574 |
| **Ordering cost ($)** | D1 | 2,000 | 2,500 | 2,300 | 2,500 | 2,600 | 2,600 |
| | D2 | 2,100 | 2,600 | 2,300 | 2,700 | 2,700 | 2,400 |
| | D3 | 2,000 | 2,200 | 2,600 | 2,600 | 2,500 | 2,700 |
| | D4 | 1,800 | 2,500 | 2,000 | 2,500 | 2,400 | 2,200 |
| | D5 | 2,100 | 3,100 | 2,700 | 2,900 | 3,000 | 2,800 |
| | D6 | 2,100 | 2,400 | 2,700 | 2,400 | 2,400 | 2,600 |
| | D7 | 2,000 | 2,500 | 2,600 | 2,500 | 2,500 | 2,400 |
| | D8 | 2,000 | 2,600 | 2,300 | 2,600 | 2,600 | 2,600 |
| | D9 | 2,100 | 2,500 | 2,500 | 2,500 | 2,500 | 2,600 |
| | D10 | 2,300 | 2,500 | 2,600 | 2,600 | 2,500 | 2,500 |
| | D11 | 2,300 | 2,600 | 2,800 | 2,700 | 2,600 | 2,800 |
| | D12 | 2,000 | 2,700 | 2,400 | 2,700 | 2,700 | 2,900 |
| | D13 | 2,000 | 2,300 | 2,200 | 2,400 | 2,500 | 2,000 |
| | D14 | 2,300 | 2,900 | 2,700 | 2,900 | 2,900 | 2,700 |
| | D15 | 2,100 | 2,200 | 2,300 | 2,200 | 2,400 | 2,300 |
| | Avg. | **2,080** | 2,540 | 2,467 | 2,580 | 2,587 | 2,540 |
| **Shortage cost ($)** | D1 | 60,593 | 46,492 | 37,052 | 44,722 | 0 | 0 |
| | D2 | 0 | 0 | 10,797 | 0 | 12,331 | 0 |
| | D3 | 0 | 0 | 46,728 | 0 | 531 | 0 |
| | D4 | 0 | 1,062 | 7,906 | 0 | 0 | 0 |
| | D5 | 118 | 0 | 120,124 | 0 | 0 | 44,840 |
| | D6 | 61,242 | 0 | 89,857 | 0 | 0 | 0 |
| | D7 | 0 | 0 | 0 | 0 | 0 | 0 |
| | D8 | 0 | 0 | 0 | 34,338 | 0 | 0 |
| | D9 | 402,498 | 354 | 0 | 6,844 | 0 | 0 |
| | D10 | 96,878 | 13,039 | 0 | 0 | 1,239 | 0 |
| | D11 | 5,841 | 0 | 0 | 0 | 0 | 0 |
| | D12 | 250,160 | 17,995 | 23,305 | 18,526 | 18,113 | 0 |
| | D13 | 0 | 0 | 0 | 0 | 10,856 | 0 |
| | D14 | 41,182 | 0 | 0 | 0 | 0 | 0 |
| | D15 | 23,069 | 0 | 3,599 | 0 | 0 | 0 |
| | Avg. | 62,772 | 5,263 | 22,625 | 6,962 | **2,871** | 2,989 |
| **Total cost ($)** | D1 | 78,686 | 61,767 | 54,258 | 60,028 | 17,452 | 17,178 |
| | D2 | 18,044 | 16,575 | 28,304 | 16,891 | 28,646 | 16,323 |
| | D3 | 18,413 | 17,785 | 62,909 | 16,694 | 16,632 | 17,455 |
| | D4 | 19,843 | 17,241 | 25,161 | 16,491 | 17,009 | 17,761 |
| | D5 | 18,835 | 15,498 | 136,312 | 15,843 | 14,895 | 61,098 |
| | D6 | 81,656 | 18,264 | 106,265 | 17,833 | 18,830 | 17,526 |
| | D7 | 19,153 | 17,176 | 17,774 | 17,496 | 17,455 | 17,867 |
| | D8 | 19,269 | 16,577 | 16,474 | 50,527 | 16,686 | 17,159 |
| | D9 | 421,308 | 17,102 | 17,339 | 23,526 | 17,127 | 17,047 |
| | D10 | 114,898 | 30,126 | 16,574 | 17,510 | 17,552 | 16,908 |
| | D11 | 24,416 | 17,414 | 15,964 | 17,603 | 17,454 | 17,353 |
| | D12 | 268,432 | 34,766 | 40,599 | 35,314 | 34,802 | 16,637 |
| | D13 | 18,289 | 16,071 | 17,442 | 16,181 | 27,278 | 17,227 |
| | D14 | 59,923 | 15,993 | 16,999 | 16,039 | 15,962 | 15,824 |
| | D15 | 41,603 | 16,961 | 20,677 | 17,858 | 18,279 | 18,180 |
| | Avg. | 81,518 | 21,954 | 39,537 | 23,722 | **19,737** | 20,103 |

Table 5.7

The average total inventory cost of all data sets and cost saving of all models compared to stochastic EOQ model

| Inventory cost | Holding cost | | Ordering cost | | Shortage cost | | Total cost | |
|---|---|---|---|---|---|---|---|---|
| | ($) | Saving (%) | ($) | Saving (%) | ($) | Saving (%) | ($) | Saving (%) |
| Stochastic EOQ | 16,666 | - | 2,080 | - | 62,772 | - | 81,518 | - |
| FIS | **14,152** | **15.1** | 2,540 | -22.1 | 5,263 | 91.6 | 21,954 | 73.1 |
| FIS+ANN | 14,445 | 13.3 | 2,467 | -18.6 | 22,625 | 64.0 | 39,537 | 51.5 |
| FIS+ANFIS_Trap | 14,180 | 14.9 | 2,580 | -24.0 | 6,962 | 88.9 | 23,722 | 70.9 |
| FIS+ANFIS_Gauss | 14,279 | 14.3 | 2,587 | -24.4 | **2,871** | **95.4** | **19,737** | **75.8** |
| FIS+ANFIS_Bell | 14,574 | 12.6 | 2,540 | -22.1 | 2,989 | 95.2 | 20,103 | 75.3 |

# CHAPTER 6
# CONCLUSIONS AND RECOMMENDATIONS

In this chapter, the conclusions of the proposed models application to process control and inventory control, which have uncertain inputs are presented. Then, the further research and recommendations of the proposed models are presented and discussed in the following subsections.

## 6.1 Conclusion for process control application

Fuzzy inference system (FIS) model, ANFIS models and ANN model were proposed for solving a process control of the plaster manufacturing system problem with uncertain conditions. Roller mill current, blower hot air flow current, classifier speed, temperature were inputs and combined water was output of the system. For FIS model, linguistic values were adapted for all fuzzy inputs and output. Fuzzy rules were designed basing on the historical experience of a case study plant. Five data sets of input data were utilized to determine the membership functions of the FIS models at different ranges of parameters.

The ANFIS models were developed by 3 membership functions; trapezoidal and triangular, Gaussian and bell shape called the ANFIS_Trap model, ANFIS_Gauss model and ANFIS_Bell model, respectively. The ANFIS models and ANN model were proposed by using the process parameters to train and test until achieving to lowest error. Then the ANFIS models and ANN model were applied to find out the suitable process control parameters. All approaches were compared with the existing process parameters.

The result has shown that the best performance parameters achieved by ANFIS_Bell model. Then the process control parameters were adjusted according to all models and further collected additional data for verification from next process which was plasterboard production process. The results after implementation to process control parameters represented that the ANFIS_Bell model obtained the lowest defects rate and can improved plasterboard production process.

## 6.2 Conclusion for inventory control application

Fuzzy Inventory System (FIS) model, FIS+ANN model and FIS+ANFIS models were proposed for solving a dynamic inventory lot-sizing problem with unpredictable conditions. Demand and supply were inputs and order quantity was output of the system. For FIS model, linguistic values were applied for both fuzzy inputs and outputs. Fuzzy rules were devised depending on the historical knowledge of a case study factory. Fifteen data sets originating from the distribution of the demand and supply of the case study factory were applied to evaluate the membership functions of the FIS model at different ranges of parameters. The appropriate ranges for the inputs of the FIS model were justified.

The output from FIS model was entered to the evaluation algorithm and calculated the total inventory cost. Then the output of FIS model was used as the input of the developed models, FIS+ANN model and FIS+ANFIS models. The FIS+ANFIS models were divided to 3 membership functions; trapezoidal and triangular, Gaussian and bell shape called the FIS+ANFIS_Trap model, FIS+ANFIS_Gauss model and FIS+ANFIS_Bell model, respectively.

The results from FIS+ANFIS models gave better values for prediction in terms of $R^2$, *RMSE* and *MAE*. The predicted values showed good fit, but when output data was entered to the evaluation algorithm of inventory model, the best total inventory cost saving compared to stochastic EOQ model was achieved by the FIS+ANFIS_Gauss model. The research emphasized that application of FIS with ANFIS was beneficial for the inventory system and that FIS+ANFIS with Gaussian membership function achieved the best performance.

## 6.3 Conclusion for both industrial applications

From the comparison study of both industrial applications, the conclusion can be described as;

(1) For the continuous data control application such as process control, ANFIS model was appropriated to implement because of achieving the best performance of prediction accuracy and this model can reduce production defects.

(2) For discontinuous data control application such as inventory control, FIS+ANFIS model was suitable to implement because of achieving the best performance of prediction accuracy and this model can reduce the inventory costs. Furthermore, the combination model of FIS with ANFIS was the first attempt to present for implementation in the manufacturing system.

## 6.4 Further research and recommendations

In further extended studies, the output of the model should be considered with linear output for both applications. For inventory control, fuzzy reorder point or fuzzy lead time should be studied and an evaluation algorithm should also be adjusted according to the realistic situation in the future study. For process control, process parameters should be adjusted following to the pragmatic condition.

The proposed models may further study by comparing with the design of experiment (DOE) method to find out for the best performance and faster of evaluation time.

# REFERENCES

Abghari, S.Z., and Sadi, M. (2013). Application of adaptive neuro-fuzzy inference system for the prediction of the yield distribution of the main products in the steam cracking of atmospheric gasoil. **Journal of the Taiwan Institute of Chemical Engineers, 44**, 365–376.

Abiyev, R.H., Kaynak, O., Alshanableh, T., and Mamedov, F. (2011). A comparative study on modelling material removal rate by ANFIS and polynomial methods in electrical discharge machining process. **Computers & Industrial Engineering, 79**, 27–41.

Aengchuan, P., and Phruksaphanrat, B. (2013). Inventory system design by fuzzy logic control: A case study. **Advanced Materials Research, 8**, 619–624.

Aengchuan, P., and Phruksaphanrat, B. (2015). Comparison of fuzzy inference system (FIS), FIS with artificial neural networks (FIS + ANN) and FIS with adaptive neuro-fuzzy inference system (FIS + ANFIS) for inventory control. **Journal of Intelligent Manufacturing**. http://link.springer.com/article/10.1007/s10845-015-1146-1.

Andriolo, A., Battini, D., Grubbstrom, R. W., and Persona, A. (2014). A century of evolution from Harris's basic lot size model: Survey and research agenda. **The International Journal of Production Economics, 155**, 16–38.

Al-Ghamdi, K., and Taylan, O. (2015). A type-2 neuro-fuzzy system based on clustering and gradient techniques applied to system identification and channel equalization. **Applied Soft Computing, 11**, 1396–1406.

Aloulou, M. A., Dolgui, A., and Kovalyov, M. Y. (2014). A bibliography of non-deterministic lot-sizing models. **International Journal of Production Research, 52, 8**, 2293–2310.

Astudillo, L., Castillo, O., Melin, P., Alanis, A., Soria, J., and Aguilar, L.T. (2006). Intelligent control of an autonomous mobile robot using type-2 fuzzy logic. **Journal of Engineering Letters, 13, 2**, 93–97.

Azedegan, A., Porobic, L., Ghazinoory, S., Samouei, P., and Kheirkhah, A. S. (2011). Fuzzy logic in manufacturing: A review of literature and a specialized application. **International Journal of Production Economics, 132, 2**, 258–270.

Azizi, A., Ali, A. Y., and Ping, L. W. (2013). An adaptive neuro-fuzzy inference system for a dynamic production environment under uncertainties. **World Applied Sciences Journal, 25, 3**, 428–433.

Bai, Y., and Wang, D. (2006). Fundamentals of Fuzzy Logic Control–Fuzzy Sets, Fuzzy Rules and Defuzzifications. In **Advanced Fuzzy Logic Technologies in Industrial Applications** (pp. 17–36). Springer London.

Camastra, F., Ciaramella, A., Giovannelli, V., Lener, M., Rastelli, V., Staiano, A., et al. (2015). A fuzzy decision system for genetically modified plant environmental risk assessment using Mamdani inference. **Expert Systems with Applications, 42**, 1710–1716.

Castillo, O., and Melin, P. (2008). **Type-2 fuzzy logic theory and applications**. Berlin: Springer.

Chaudhary, H., Panwar, V., Prasad, R., and Sukavanam, N. (2014). Adaptive neuro fuzzy based hybrid force/position control for anindustrial robot manipulator. **Journal Of Intelligent Manufacturing**. doi:10.1007/s10845-014-0952-1.

Chede, B., Jain, C. K., Jain, S. K., and Chede, A. (2012). Fuzzy logic analysis based on inventory considering demand and stock quantity on hand. **Industrial Engineering Letters, 2, 1**, 13–21.

Chen, C.W. (2006). Stability conditions of fuzzy systems and its application to structural and mechanical systems. **Advances in Engineering Software, 37**, 624–629.

Chen, C.W. (2010). Application of fuzzy-model-based control to nonlinear structural systems with time delay: an LMI method. **Journal of Vibration and Control, 16, 11**, 1651–1672.

Chen, C.W., Chiang, W.L., and Hsiao, F.H. (2004). Stability analysis of T–S fuzzy models for nonlinear multiple time-delay interconnected systems. **Mathematics and Computers in Simulation, 66, 6**, 523–537.

Chen, S. P. (2011). A membership function approach to lot size re-order point inventory problems in fuzzy environments. **International Journal of Production Research, 49, 13**, 3855–3871.

Chen, S. H.,Wang, C. C., and Ramer, A. (1996). Backorder fuzzy inventory model under function principle. **Information Sciences, 95**, 71–79.

Chung, C. J., Widyadana, G. A., and Wee, H. M. (2011). Economic production quantity model for deteriorating inventory with random machine unavailability and shortage. **International Journal of Production Research, 49, 3**, 883–902.

DeMatteis, J.J. (1968). An economic lot-sizing technique I: the part period algorithm. **IBM Systems Journal, 7, 1**, 30-38.

Esen, H., Inalli, M., Sengur, A., and Esen, M. (2008a). Forecasting of a ground-coupled heat pump performance using neural networks with statistical data weighting pre-processing. **International Journal of Thermal Sciences, 47, 4**, 431–441.

Esen, H., Inalli, M., Sengur, A., and Esen, M. (2008b). Performance prediction of a ground-coupled heat pump system using artificial neural networks. **Expert Systems with Applications, 35**, 1940–1948.

Esen, H., Inalli, M., Sengur, A., and Esen, M. (2008c). Modelling a ground-coupled heat pump system using adaptive neuro-fuzzy inference systems. **International Journal of Refrigeration, 31, 1**, 65–74.

Esen, H., Inalli, M., Sengur, A., and Esen, M. (2008d). Artificial neural networks and adaptive neuro-fuzzy assessments for ground coupled heat pump system. **Energy and Buildings, 40, 6**, 1074–1083.

Esen, H., Inalli, M., Sengur, A., and Esen, M. (2008e). Predicting performance of a ground-source heat pump system using fuzzy weighted pre-processing-based ANFIS. **Building and Environment, 43, 12**, 2178–2187.

Esen, H., Ozgen, F., Esen, M., and Sengur, A. (2009). Artificial neural network and wavelet neural network approaches for modelling of a solar air heater. **Expert Systems with Applications, 36, 8**, 11240–11248.

Feng, G. (2010). Integrating dynamic pricing and replenishment decisions under supply capacity uncertainty. **Management Science, 56, 2**, 2154–2172.

Fragiadakis, N. G., Tsoukalas, V. D., and Papazoglou, V. J. (2014). An adaptive neuro-fuzzy inference system (anfis) model for assessing occupational risk in the shipbuilding industry. **Safety Science, 63**, 226–235.

Glock, C. H., Grosse, E. H., and Ries, J. M. (2014). The lot sizing problem: A tertiary study. **The International Journal of Production Economics, 155**, 39–51.

Gokulachandran, J., and Mohandas, K. (2015). Comparative study of two soft computing techniques for the prediction of remaining useful life of cutting tools. **Journal of IntelligentManufacturing, 26**, 255–268. doi:10.1007/ s10845-013-0778-2.

Good, P. I. (1999). **Resampling methods: A practical guide to data analysis**. Boston: Birkhauser.

Groff, G.K. (1979). A lot-sizing rule for time phased component demand. **Production and Inventory Management. 20, 1**, 47-53.

Grubbstrom, R. W. (2014). Dynamic lot sizing with a finite production rate. **International Journal of Production Economics's, 149**, 68–79.

Guan,Y. (2011). Stochastic lot-sizing with backlogging: Computational complexity analysis. **Journal of Global Optimization's, 49**, 651–678.

Guillaume, R.,Kobylanski, P., and Zielinski, P. (2012).Arobust lot sizing problem with ill-known demands. **Fuzzy Sets and Systems, 206**, 39–57.

Guner, H. A. A., and Yumuk, H. A. (2014). Application of a fuzzy inference system for the prediction of long shore sediment transport. **Applied Ocean Research, 48**, 162–175.

Guneri, A. F., Ertay, T., and Yucel, A. (2011). An approach based on ANFIS input selection and modeling for supplier selection problem. **Expert Systems with Applications, 38**, 14907–14917.

Handfield, R., Warsing, D., and Wu, X. (2009). (Q, r) Inventory policies in a fuzzy uncertain supply chain environment. **European Journal of Operational Research, 197**, 609–619.

Harris, F. H. (1913). How many parts to make at once. **Factory, The Magazine of Management, 10(2)**, 135–136, 152.

Hosoz, M., Ertunc, H. M., and Bulgurcu, H. (2011). An adaptive neuro fuzzy inference system model for predicting the performance of a refrigeration system with a cooling tower. **Expert Systems with Applications, 38**, 14148–14155.

Hossain, M.H.J., and Ahmad, M. (2014). A neuro-fuzzy approach to select cutting parameters for commercial die manufacturing. **Procedia Engineering, 90**, 753 – 759.

Hsiao, F.H., Hwang, J.D., Chen, C.W., and Tsai, Z.R. (2005). Robust stabilization of nonlinear multiple time-delay large-scale systems via decentralized fuzzy control. **IEEE Transactions on Fuzzy Systems, 13, 1**, 152–163.

Jang, J. S. R. (1993). ANFIS: Adaptive-network-based fuzzy inference system. **IEEE Transactions on Systems, Man, Cybernetics, 23**, 665–685.

Jha, M. N., Pratihar, D. K., Bapat, A. V., Dey, V., Ali, M., and Bagchi, A. C. (2014). Knowledge-based systems using neural networks for electron beam welding process of reactive material (Zircaloy-4). **Journal of Intelligent Manufacturing, 25**, 1315–1333. doi:10.1007/s10845-013-0732-3.

Kaitwanidvilai, S., and Parnichkun, M. (2005). Force control in a pneumatic system using hybrid adaptive neuro-fuzzy model reference control. **Mechatronics**, 1523–41.

Kamal, L., and Sculfort, J.-L. (2007). Fuzzy modelling of inventory control system in uncertain environment. **International Symposium on Logistics and Industrial Informatics**, 53–57. doi:10.1109/LINDI. 2007.4343512.

Kang, H.-Y., and Lee, A. H. I. (2013). A stochastic lot-sizing model with multi-supplier and quantity discounts. **International Journal of Production Research, 51, 1**, 245–263.

Kayacan, E., Saeys, W., Kayacan, E., Ramon, H., and Kayank, O. 2012. Intelligent control of a Tractor-Implement system using type-2 fuzzy neural networks, in: **WCCI2012 IEEE World Congress on Computational Intelligence**, Brisbane, Australia, pp. 171–178.

Khan, M., Jaber, M. Y., and Wahab, M. I. M. (2010). Economic order quantity model for items with imperfect quality with learning in inspection. **International Journal of Production Economics, 124, 1**, 87–96.

Kim, D., Seo, S.J., and Park, G.T. (2005). Zero-moment point trajectory modeling of a biped walking robot using an adaptive neuro-fuzzy system. **IEE Proceedings Control Theory and Applications, 152, 4**, 411–426.

Kiran, T. R., and Rajput, S. P. S. (2011). An effectiveness model for an indirect evaporative cooling (IEC) system: Comparison of artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and fuzzy inference system (FIS) approach. **Applied Soft Computing, 11**, 3525–3533.

Kocyigit, N. (2015). Fault and sensor error diagnostic strategies for a vapor compression refrigeration system by using fuzzy inference systems and artificial neural network. **The International Journal of Refrigeration, 50**, 69–79.

Kovac, P., Rodic, D., Pucovsky, V., Savkovic, B., and Gostimirovic, M. (2013).Application of fuzzy logic and regression analysis for modeling surface roughness in face milling. **Journal of Intelligent Manufacturing, 24**, 755–762. doi:10.1007/s10845-012-0623-z.

Kuo, C.-F. J., Hsu, C.-T.M., Liu, Z.-X., and Wu, H.-C. (2014). Automatic inspection system of LED chip using two-stages back-propagation neural network. **Journal of Intelligent Manufacturing, 25**, 1235–1243.doi:10.1007/s10845-012-0725-7.

Kuo, R. J., Tseng, Y. S., and Chen, Z.-Y. (2014). Integration of fuzzy neural network and artificial immune system-based back propagation neural network for sales forecasting using qualitative and quantitative data. **Journal Of Intelligent Manufacturing**. doi:10.1007/s10845-014-0944-1.

Kurnaz, S., Cetin, O., and Kaynak, O. (2010). Adaptive neuro-fuzzy inference system based autonomous flight control of unmanned air vehicles. **Expert Systems with Applications, 37**, 1229–1234.

Lee, H., and Yao, J. (1999). Economic order quantity in fuzzy sense for inventory without backorder model. **Fuzzy Sets and Systems, 105, 1**, 13–31.

Lee, S.-D., Yang, C.-M., and Lan, S.-C. (2014). Economic lot sizing in a production system with random demand. **International Journal of Systems Science**. doi:10.1080/00207721.2014.915354.

Lenart, B., Grzybowska, K., and Cimer, M. (2012). Adaptive inventory control in production systems. In E. Corchado et al. (Eds.), HAIS 2012, Part II, LNCS. 7209. Springer: Berlin, Heidelberg (pp. 222–228).

Li, H., and Thorstenson, A. (2014).Amulti-phase algorithm for a joint lot sizing and pricing problem with stochastic demands. **International Journal of Production Research, 52, 8**, 2345–2362.

Li, Y., and Liu, Y. (2006). Real-Time tip-over prevention and path following control for redundant nonholonomic mobile modular manipulators via fuzzy and neural-fuzzy approaches. **Journal of Dynamic Systems, Measurement and Control1, 28**, 753–764.

Mahata, G.C., and Goswami,A. (2013). Fuzzy inventory models for items with imperfect quality and shortage backordering under crisp and fuzzy decision variables. **Computer and Industrial Engineering, 64**, 190–199.

Mahdaoui, R., Mouss, L.H., Kadri, O., Mouss, M.D., and Chouhal, O. 2012. Fault prognosis by temporal neuro-fuzzy systems: application for manufacturing systems, in: **Proceedings of IEEE Sciences of Electronics, Technologies of Information and Telecommunications (SETIT)**, Sousse, Tunisia, pp. 1–6.

Mamdani, E. H., and Assilian, S. (1975). An experiment in linguistic synthesis with fuzzy logic controller. **International Journal of Man-Machine Studies, 7**, 1–13.

Marza, D., Seyyedi, D., and Capretz, L.F. (2008). Estimation development time of software projects using a neuro fuzzy approach. **World Academy of Science, Engineering and Technology, 22**, 575–579.

Melin, P., Soto, J., Castillo, O., and Soria, J. (2012). A new approach for time series prediction using ensembles of ANFIS models. **Expert Systems with Applications, 39**, 3494–3506.

Meredith, J., and Shafer, S. (2011). **Operations management** (4th ed.). Hoboken: Wiley.

Mondal, S., and Maiti, M. (2002). Multi-item fuzzy EOQ models using genetic algorithm. **Computers & Industrial Engineering, 44, 1**, 105–117.

Nasrollahzadeh,K.,and Basiri, M. M. (2014). Prediction of shear strength of FRP reinforced concrete beams using fuzzy inference system. **Expert Systems with Applications, 41**, 1006–1020.

Ouyang, C.S., Lee, W.J., and Lee, S.J. (2005). A TSK-Type Neurofuzzy Network Approach to System Modeling Problems. **IEEE Transactions on Systems, Man and Cybernetics – Part B: Cybernetics, 35, 4**, 751–767.

Özkan, G., and Inal, M. (2014). Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems. **Applied Soft Computing, 24**, 232–238.

Pani, A.K., and Mohanta, H.K. (2014). Soft sensing of particle size in a grinding process: Application of support vector regression, fuzzy inference and adaptive neuro fuzzy inference techniques for online monitoring of cement fineness. **Powder Technology, 264**, 484–497.

Park, K. S. (1987). Fuzzy set theoretic interpretation of economic order quantity. **IEEE Transactions on Systems, Man and Cybernetics, 6, 17**, 1082–1084.

Parlar, M., and Perry, D. (1995). Analysis of a (Q, r, T) inventory policy with deterministic and random yields when future supply is uncertain. **European Journal of Operational Research, 84**, 431–443.

Patrick, D.R., and Fardo, S.W. (1997). **Industrial Process Control systems**. Delmar Publishers, Albany, New York.

Petković, D., Pavlović, N.T., Shamshirband, S., Kiah, M.L.M, Anuar, N.B., and Idris, M.Y.I. (2014). Adaptive neuro-fuzzy estimation of optimal lens system parameters. **Optics and Lasers in Engineering, 55**, 84–93.

Phootrakornchai,W., and Jiriwibhakorn, S. (2015). Online critical clearing time estimation using an adaptive neuro-fuzzy inference system (ANFIS). **Electrical Power and Energy Systems, 73**, 170–181.

Phruksaphanrat, B., and Tanthatemee, T. (2013). Fuzzy Logic Approach to Inventory Lot-Sizing Problem Under Uncertain Environment. in **G.-C. Yang et al. (eds.), IAENG Transactions on Engineering Technologies, Lecture Notes in Electrical Engineering, 186**. doi: 10.1007/978-94-007-5651-9_15.

Porteus, E. L. (1986). Optimal lot sizing, process quality improvement and set up cost reduction. **Operations Research, 34, 1**, 137–144.

Razani, M., Yazdani-Chamzini, A., and Yakhchali, S. H. (2013). A novel fuzzy inference system for predicting roof fall rate in underground coal mines. **Safety Science, 55**, 26–33.

Rong, L. (2010). Uncertain economic order quantity model with uncertain costs. **Journal of Information and Computational Science, 7, 13**, 2723–2730.

Rothstein, A. P., and Rakityanskaya, A. B. (2006). Inventory control as an identification problem based on fuzzy logic. **Cybernetics and Systems Analysis, 42, 3**, 411–419.

Roy, S.S. (2005). Design of adaptive neuro-fuzzy inference system for predicting surface roughness in turing operation. **Journal of Scientific and Industrial Research, 64**, 1087–1094.

Samanta, B., and Al-Araimi, S. A. (2001). An inventory control model using fuzzy logic. **The International Journal of Production Economics, 73**, 217–226.

Samanta, B., and Al-Araimi, S. A. (2003). Application of an adaptive neuro-fuzzy inference system in inventory control. **International Journal of Smart Engineering System Design, 5, 4**, 547–553.

Sana, S. S. (2011). Price-sensitive demand for perishable items—An EOQ model. **Applied Mathematics and Computation, 217, 13**, 6248–6259.

Seneyigit, E., and Erol, R. (2010). New lot sizing heuristics for demand and price uncertainties with service-level constraint. **International Journal of Production Research, 48, 1**, 21–44.

Seyedhoseini, S.M., Jassbi, J., and Pilevari, N. (2010). Application of adaptive neuro fuzzy inference system in measurement of supply chain agility: real case study of a manufacturing company. **African Journal of Business Management, 4, 1**, 083–096.

Shamshirband, S., Petkovic, D., Hashim, R., Motamedi, S., and Anuar, N.B. (2014). An appraisal of wind turbine wake models by adaptive neuro-fuzzy methodology. **Electrical Power and Energy Systems, 63**, 618–624.

Silver, E. A., and Meal, H. A. (1973). A heuristic for selecting lot sizing requirements for the case of a deterministic time varying demand rate and discrete opportunities for replenishment. **Production and Inventory Management, 14, 2**, 64–74.

Sipper, D. and Bulfin, R.L. (1998). **Production planning control and integration**. McGraw-Hill International Editions, Singapore.

Sommer, G. (1981). Fuzzy inventory scheduling. In G. Lasker (Ed.), **Applied systems and cybernetics**. New York: Pergamon Press.

Subbaraj, P., and Kannapiran, B. (2014). Fault detection and diagnosis of pneumatic valve using Adaptive Neuro-Fuzzy Inference System approach. **Applied Soft Computing, 19**, 362–371.

Sumathi, S., and Paneerselvam, S. (2010). **Computational intelligence paradigms: Theory and applications using MATLAB**. Boca Raton, FL: CRC Press, Inc.

Taft, E. W. (1918). The most economical production lot. **The Iron Age, 101**, 1410–1412.

Tanthatemee, T., and Phruksaphanrat, B. (2012). Fuzzy inventory control for uncertain demand and supply. **Proceedings of the International Multi Conference of Engineers and Scientists, 2**, 1224–1229.

Tettey, T., and Marwala, T. 2006. Neuro-fuzzy modeling and fuzzy rule extraction applied to conflict management. in: **The International Conference on Neural Information Processing (ICONIP) Part III LNCS**, 4234, pp. 1087–1094.

Topalov, A.V., Kayacan, E., Oniz, Y., and Kaynak, O. 2009. Adaptive neuro-fuzzy control with sliding mode learning algorithm: application to antilock braking system. in: **7th Asian Control Conference**, Hong Kong, China, pp. 784–789.

Topalov, A.V., Oniz, Y., Kayacan, E., Kaynak, O. (2011). Neuro-fuzzy control of antilock braking system using sliding mode incremental learning algorithm. **Neuro-computing, 74**, 1883–1893.

Toy, A.O., Berk, E. (2013). Dynamic lot sizing for a warm/cold process: Heuristics and insights. **The International Journal of Production Economics. 145**, 53-66.

Tsai, K.-M., and Luo, H.-J. (2014). An inverse model for injection molding of optical lens using artificial neural network coupled with genetic algorithm. **Journal of Intelligent Manufacturing**. doi:10.1007/s10845-014-0999-z

Ullah, M., and Kang, C. W. (2014). Effect of rework, rejects and inspection on lot size with work-in-process inventory. **International Journal Production Research, 52, 8**, 2448–2460.

Vesselenyi, T., Dzitac, S., Dzitac, I., and Manolescu, M.J. (2007). Fuzzy and neural controllers for a pneumatic actuator. **International Journal of Computers Communications & Control, 2, 4**, 375–387.

Vollmann, T.E., Berry, W.L., and Whybark, D.C. (1997). **Manufacturing Planning and Control Systems**, 4$^{th}$ edition. McGraw-Hill.

Wagner, H. M., and Whitin, T. M. (1958). Dynamic version of the economic lot size model. **Manangement Science, 5, 1**, 89–96.

Wang, B., Man, T., and Jin, H. (2015). Prediction of expansion behavior of self-stressing concrete by artificial neural networks and fuzzy inference systems. **Construction and Building Materials, 84**, 184–191.

Wang, C.-H. (2010). Some remarks on an optimal order quantity and reorder point when supply and demand are uncertain. **Computers & Industrial Engineering, 58**, 809–813.

Wang, W., Ismail, F., and Golnaraghi, A.F. (2004). A neuro-fuzzy approach to gear system monitoring. **IEEE Transactions on Fuzzy Systems, 12, 5**, 710–723.

Wee, H. M., and Widyadana, G. A. (2012). Economic production quantity models for deteriorating items with rework and stochastic preventive maintenance time. **International Journal Production Research, 50, 11**, 2940–2952.

Yang, L., and Entchev, E. (2014). Performance prediction of a hybrid micro generation system using adaptive neuro-fuzzy inference system (ANFIS) technique. **Applied Energy, 134**, 197–203.

Yang, S.M., Tung, Y.J., and Liu, Y.C. (2005). A Neuro-fuzzy system design methodology for vibration control. **Asian Journal of Control, 7, 4**, 393–400.

Yang, W.-A., and Zhou, W. (2013). Autoregressive coefficient-invariant control chart pattern recognition in auto correlated manufacturing processes using neural network ensemble. **Journal of Intelligent Manufacturing**. doi:10.1007/ s10845-013-0847-6

Yeh, K., Chen, C.W., Lo, D.C., Liu, K.F.R. (2012). Neural-network fuzzy control for chaotic tuned mass damper systems with time delays. **Journal of Vibration and Control, 18, 6**, 785–795.

Yimer, A.D., and Demirli, K. (2004). Fuzzy modeling and simulation of single item inventory system with variable demand. **IEEE annual meeting of the North**

**American fuzzy information processing society Banff, 2, Alberta**, Canada (pp. 985–989).

Ying, L. C., and Pan, M. C. (2008). Using adaptive network based fuzzy inference system to forecast regional electricity loads. **Energy Conversation and Management, 49**, 205–211.

Zhou, Q., Chan, C.W., Tontiwachwuthikul, P., Idem, R., and Gelowitz, D. (2013). Application of neuro-fuzzy modeling technique for operational problem solving in a $CO_2$ capture process system. **International Journal of Greenhouse Gas Control, 15**, 32–41.

# APPENDICES

# APPENDIX A

## Inputs data for process control application

Janurary 2015

| Data | $R$ | $B$ | $C$ | $T$ | $CW$ | Data | $R$ | $B$ | $C$ | $T$ | $CW$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 51.5 | 53.3 | 260 | 145.8 | 6 | 51 | 55.3 | 50.4 | 255 | 145.5 | 6.14 |
| 2 | 51.2 | 52.7 | 260 | 154.5 | 5.6 | 52 | 56.3 | 50.6 | 255 | 150.8 | 5.8 |
| 3 | 52.3 | 51.8 | 260 | 152.4 | 5.58 | 53 | 55.4 | 50.9 | 255 | 148.4 | 5.95 |
| 4 | 50.5 | 52.8 | 260 | 151 | 5.56 | 54 | 56.9 | 50.6 | 255 | 149.1 | 5.87 |
| 5 | 57.4 | 51 | 260 | 153.7 | 5.92 | 55 | 56.2 | 50.9 | 255 | 145.6 | 6.17 |
| 6 | 52.9 | 51.7 | 260 | 156.3 | 5.45 | 56 | 59.9 | 49.1 | 255 | 159 | 5.74 |
| 7 | 53.4 | 50.9 | 260 | 155 | 5.83 | 57 | 56.6 | 50.7 | 255 | 153.7 | 5.94 |
| 8 | 52 | 52 | 260 | 151 | 5.7 | 58 | 59.1 | 50 | 255 | 147 | 6.16 |
| 9 | 51.5 | 51.8 | 260 | 151.8 | 5.61 | 59 | 55.9 | 50.4 | 255 | 144.9 | 6.2 |
| 10 | 53.1 | 51.6 | 260 | 150 | 5.88 | 60 | 56.4 | 50.5 | 255 | 148.5 | 5.9 |
| 11 | 53.9 | 50.7 | 260 | 150.9 | 5.65 | 61 | 56.3 | 50.2 | 255 | 146.5 | 6.18 |
| 12 | 53 | 50.8 | 260 | 148.6 | 5.99 | 62 | 55.4 | 51.1 | 255 | 152 | 5.7 |
| 13 | 50.5 | 51.6 | 260 | 149.7 | 5.82 | 63 | 56.7 | 51.8 | 255 | 147.3 | 6 |
| 14 | 55.5 | 51.1 | 260 | 150.7 | 5.75 | 64 | 55.1 | 51.7 | 255 | 148.6 | 6.04 |
| 15 | 50.4 | 50.6 | 260 | 154 | 5.48 | 65 | 55.5 | 51.3 | 255 | 150 | 5.75 |
| 16 | 51.5 | 50.3 | 260 | 155.4 | 5.72 | 66 | 56 | 51.5 | 255 | 147.7 | 6 |
| 17 | 57 | 49.3 | 260 | 152.3 | 6.1 | 67 | 54.3 | 51.8 | 255 | 148.7 | 6.02 |
| 18 | 51.4 | 51.2 | 260 | 147.9 | 5.9 | 68 | 51.3 | 52.1 | 255 | 143.9 | 6.2 |
| 19 | 52.6 | 52 | 260 | 148.1 | 5.45 | 69 | 50.8 | 52.2 | 255 | 143.8 | 6.18 |
| 20 | 57 | 51.1 | 260 | 147.4 | 6.15 | 70 | 56.8 | 50.7 | 255 | 150.9 | 5.95 |
| 21 | 55.9 | 51.8 | 260 | 145 | 6.25 | 71 | 49.2 | 52.7 | 255 | 145.2 | 6.15 |
| 22 | 52.5 | 51.8 | 260 | 145.8 | 6.07 | 72 | 50.7 | 50.7 | 255 | 141.7 | 6.2 |
| 23 | 50.6 | 51.5 | 260 | 148.9 | 5.85 | 73 | 51.4 | 51.1 | 255 | 138.3 | 6.2 |
| 24 | 48 | 51.7 | 260 | 148.5 | 6.05 | 74 | 50.3 | 52 | 255 | 141.1 | 6.17 |
| 25 | 48.8 | 52 | 260 | 150.3 | 5.72 | 75 | 50.4 | 51.5 | 255 | 150.3 | 5.74 |
| 26 | 49 | 51.9 | 260 | 146.1 | 6 | 76 | 54.7 | 49.8 | 255 | 140 | 6.2 |
| 27 | 48.7 | 52.1 | 260 | 145.8 | 6.15 | 77 | 46.8 | 52.9 | 255 | 149.5 | 5.8 |
| 28 | 49.6 | 52.1 | 260 | 147.8 | 5.59 | 78 | 48.7 | 52.5 | 245 | 148.9 | 6.2 |
| 29 | 50.9 | 52.2 | 260 | 151.3 | 5.6 | 79 | 46.6 | 52.4 | 245 | 148.8 | 6.24 |
| 30 | 37 | 53.8 | 260 | 146.4 | 6.1 | 80 | 48.1 | 52.3 | 245 | 149.4 | 6.2 |
| 31 | 55.5 | 51.3 | 260 | 144.7 | 5.69 | 81 | 45.1 | 56.6 | 245 | 155.8 | 5.72 |
| 32 | 58.7 | 49.7 | 260 | 141.6 | 6.22 | 82 | 52.1 | 51 | 245 | 141.4 | 6.25 |
| 33 | 55.5 | 51.1 | 260 | 145.5 | 6.15 | 83 | 47.7 | 51.5 | 245 | 143 | 6.23 |
| 34 | 54.4 | 52.3 | 260 | 148.8 | 5.88 | 84 | 45.1 | 51.8 | 245 | 151.7 | 5.8 |
| 35 | 55.2 | 51.9 | 260 | 148.9 | 5.92 | 85 | 44.1 | 52.4 | 245 | 153.3 | 5.3 |
| 36 | 51.6 | 51.3 | 260 | 150.5 | 5.65 | 86 | 53.5 | 49.8 | 245 | 156.9 | 5.25 |
| 37 | 53.8 | 51.3 | 260 | 150 | 5.53 | 87 | 50.5 | 50.9 | 245 | 154.9 | 5.1 |
| 38 | 61.1 | 51.2 | 255 | 144.1 | 6.3 | 88 | 48.5 | 51.8 | 245 | 147.7 | 6.26 |
| 39 | 57.1 | 51.8 | 255 | 161.6 | 5.73 | 89 | 46.3 | 52 | 245 | 148.2 | 6.18 |
| 40 | 55.7 | 51.5 | 255 | 145.9 | 6.15 | 90 | 46.1 | 51.2 | 245 | 150.6 | 6 |
| 41 | 56 | 51.3 | 255 | 153 | 5.82 | 91 | 44.7 | 51.3 | 245 | 148.5 | 6.22 |
| 42 | 57.2 | 51.1 | 255 | 150.8 | 5.75 | 92 | 48.6 | 51.9 | 245 | 147.4 | 6.24 |
| 43 | 57.4 | 52.1 | 255 | 156.6 | 5.3 | 93 | 45.5 | 51.5 | 245 | 150.5 | 5.95 |
| 44 | 57.2 | 51 | 255 | 154.7 | 5.59 | 94 | 46 | 52.3 | 245 | 153.3 | 5.45 |
| 45 | 57.2 | 50.9 | 255 | 151.5 | 5.86 | 95 | 46.8 | 52.1 | 245 | 148.2 | 6.16 |
| 46 | 53.4 | 50.4 | 255 | 151.7 | 5.65 | 96 | 46 | 51.8 | 245 | 140.5 | 6.22 |
| 47 | 40.5 | 51.1 | 255 | 153.5 | 5.64 | 97 | 45.7 | 51.7 | 245 | 141.1 | 6.22 |
| 48 | 54.7 | 51.1 | 255 | 147.3 | 6.1 | 98 | 45.9 | 51.9 | 245 | 142.3 | 6.23 |
| 49 | 54.4 | 51 | 255 | 148.2 | 6.06 | 99 | 47.5 | 50.4 | 245 | 142.3 | 6.22 |
| 50 | 51.9 | 51.2 | 255 | 145.4 | 6.1 | 100 | 47.3 | 50.4 | 245 | 142.1 | 6.19 |

$R$ = roller mill current (Ampere), $B$ = blower air flow current (Ampere), $C$ = classifier speed (rpm)
$T$ = temperature (C), $CW$ = actual combined water

February 2015

| Data | $R$ | $B$ | $C$ | $T$ | $CW$ | Data | $R$ | $B$ | $C$ | $T$ | $CW$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 47.6 | 50.8 | 245 | 142.4 | 6.2 | 51 | 60.1 | 53 | 255 | 145 | 6.18 |
| 2 | 49.8 | 54 | 250 | 149.3 | 5.89 | 52 | 55.3 | 54.9 | 255 | 149.3 | 5.47 |
| 3 | 43.8 | 54.1 | 250 | 150.9 | 5.63 | 53 | 58.1 | 53.7 | 255 | 149.1 | 5.89 |
| 4 | 43.9 | 53.8 | 250 | 150.6 | 5.93 | 54 | 54.4 | 54.2 | 255 | 149.4 | 5.82 |
| 5 | 53.9 | 52.5 | 250 | 154.1 | 5.49 | 55 | 55.7 | 53.9 | 255 | 145.9 | 5.96 |
| 6 | 48.3 | 52.4 | 250 | 150.9 | 5.68 | 56 | 55.4 | 54 | 255 | 148.5 | 6 |
| 7 | 50.3 | 53.1 | 250 | 146.1 | 5.48 | 57 | 55.4 | 54 | 255 | 149.1 | 5.85 |
| 8 | 50.6 | 52.4 | 250 | 147.6 | 5.96 | 58 | 59.3 | 53.2 | 255 | 150 | 5.51 |
| 9 | 48.6 | 52.8 | 250 | 148.8 | 5.93 | 59 | 56.1 | 54.2 | 255 | 149.7 | 5.83 |
| 10 | 50.4 | 52.6 | 250 | 154.5 | 5.81 | 60 | 53.8 | 54.3 | 255 | 148 | 6.06 |
| 11 | 50.7 | 52.9 | 250 | 148.2 | 6 | 61 | 53.7 | 54.2 | 255 | 151.7 | 5.52 |
| 12 | 50.9 | 53.1 | 250 | 147.5 | 6.05 | 62 | 55.6 | 54.3 | 255 | 151 | 5.75 |
| 13 | 48.3 | 53.5 | 250 | 146.2 | 5.96 | 63 | 60.7 | 53.1 | 255 | 150.6 | 6 |
| 14 | 60.3 | 50.9 | 250 | 147.1 | 6.1 | 64 | 50.8 | 55.2 | 255 | 149.9 | 5.57 |
| 15 | 43.8 | 53.4 | 250 | 148 | 5.98 | 65 | 55.6 | 54.8 | 255 | 149.7 | 5.8 |
| 16 | 45.1 | 52.9 | 250 | 152.1 | 5.98 | 66 | 56.1 | 55 | 255 | 150.9 | 5.78 |
| 17 | 59.8 | 69.1 | 250 | 141.1 | 6.17 | 67 | 55.5 | 54.1 | 255 | 151.8 | 5.77 |
| 18 | 52.3 | 58.2 | 250 | 136.9 | 6.08 | 68 | 56.9 | 54.3 | 255 | 153.2 | 5.84 |
| 19 | 60.7 | 56.6 | 250 | 145.5 | 6.15 | 69 | 55.2 | 54.6 | 255 | 152 | 5.64 |
| 20 | 50.7 | 57 | 250 | 137.2 | 6.18 | 70 | 56.6 | 53.8 | 255 | 151 | 5.99 |
| 21 | 48.4 | 58.4 | 250 | 153.3 | 5.33 | 71 | 55.1 | 53.9 | 255 | 149.7 | 5.78 |
| 22 | 57.6 | 56.8 | 250 | 141.1 | 5.77 | 72 | 55.6 | 53.8 | 255 | 151.2 | 5.74 |
| 23 | 49.5 | 57.1 | 250 | 141.1 | 6.19 | 73 | 55.5 | 53.5 | 255 | 152.1 | 5.87 |
| 24 | 48.6 | 57.5 | 250 | 139.4 | 6.2 | 74 | 54.5 | 54 | 255 | 151.4 | 5.58 |
| 25 | 53.5 | 56.6 | 250 | 139.4 | 5.96 | 75 | 54.7 | 53.9 | 255 | 151.9 | 5.61 |
| 26 | 54.7 | 56.6 | 250 | 141.7 | 6.25 | 76 | 52.1 | 55 | 255 | 149.1 | 6 |
| 27 | 58 | 55.3 | 250 | 150.2 | 5.92 | 77 | 57.1 | 54 | 255 | 151.3 | 5.89 |
| 28 | 58.9 | 55.5 | 250 | 132.4 | 6.3 | 78 | 54.2 | 54.8 | 255 | 150.7 | 5.53 |
| 29 | 55.4 | 55.7 | 250 | 153.4 | 5.72 | 79 | 54.7 | 54.5 | 255 | 150 | 5.95 |
| 30 | 57 | 55.3 | 250 | 134.9 | 6.16 | 80 | 56.2 | 53.7 | 255 | 148.6 | 5.92 |
| 31 | 56 | 55.2 | 250 | 158.1 | 5.68 | 81 | 54.3 | 55.5 | 255 | 148.5 | 5.93 |
| 32 | 48.7 | 55.2 | 250 | 139.3 | 6.17 | 82 | 52.1 | 71.5 | 255 | 146.8 | 5.66 |
| 33 | 56.3 | 54.7 | 250 | 138.8 | 6.23 | 83 | 49.3 | 71.5 | 255 | 147.5 | 6.14 |
| 34 | 53 | 54.3 | 250 | 143.1 | 5.67 | 84 | 55 | 71.4 | 255 | 158.7 | 5.1 |
| 35 | 55.4 | 54.2 | 250 | 137.7 | 6.25 | 85 | 59.6 | 69.2 | 255 | 155 | 5.48 |
| 36 | 56 | 54.1 | 250 | 144.8 | 6.2 | 86 | 58.9 | 69.3 | 255 | 144.1 | 6.04 |
| 37 | 48.6 | 55.6 | 250 | 159.1 | 5.44 | 87 | 60.1 | 68.1 | 255 | 144.1 | 6.17 |
| 38 | 53.6 | 53.5 | 250 | 150.8 | 5.72 | 88 | 58.1 | 68.1 | 255 | 141.1 | 5.7 |
| 39 | 50.1 | 53.2 | 250 | 148.1 | 6.02 | 89 | 54.2 | 70 | 250 | 136.9 | 6.2 |
| 40 | 50.3 | 53.3 | 250 | 155.1 | 4.7 | 90 | 52.3 | 70.4 | 250 | 140.4 | 6.18 |
| 41 | 50.6 | 53 | 250 | 155.9 | 5.1 | 91 | 63.1 | 68.3 | 250 | 143 | 6.22 |
| 42 | 52.7 | 53.1 | 250 | 155.9 | 5.26 | 92 | 60.8 | 68 | 250 | 139.4 | 6.22 |
| 43 | 51 | 52.9 | 250 | 155.6 | 5.28 | 93 | 62.3 | 68 | 250 | 142.5 | 6.25 |
| 44 | 51.8 | 52.5 | 250 | 155.5 | 5.15 | 94 | 61.8 | 68 | 250 | 145.9 | 5.84 |
| 45 | 55.2 | 53 | 250 | 149.4 | 5.9 | 95 | 62.2 | 67.7 | 250 | 145.8 | 6.12 |
| 46 | 51 | 52.2 | 250 | 153.3 | 5.8 | 96 | 62.4 | 67.7 | 250 | 158.9 | 5.74 |
| 47 | 53.7 | 53.7 | 255 | 153.3 | 5.56 | 97 | 61.8 | 68.1 | 250 | 149.8 | 5.63 |
| 48 | 58.3 | 52.7 | 255 | 148.3 | 6 | 98 | 60.8 | 68.1 | 250 | 141.4 | 6.23 |
| 49 | 55.3 | 53.2 | 255 | 148.4 | 5.68 | 99 | 60.3 | 68.6 | 250 | 148.8 | 5.95 |
| 50 | 54.9 | 53.2 | 255 | 148.2 | 5.93 | 100 | 51.4 | 52.8 | 250 | 156 | 5.31 |

$R$ = roller mill current (Ampere), $B$ = blower air flow current (Ampere), $C$ = classifier speed (rpm)
$T$ = temperature (C), $CW$ = actual combined water

March 2015

| Data | *R* | *B* | *C* | *T* | *CW* | Data | *R* | *B* | *C* | *T* | *CW* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 59.8 | 67 | 250 | 150.9 | 5.72 | 51 | 63 | 66 | 245 | 142.9 | 6.25 |
| 2 | 59.2 | 66.4 | 250 | 138.5 | 6.24 | 52 | 59 | 65 | 245 | 153.6 | 4.53 |
| 3 | 60.7 | 66.2 | 250 | 139.3 | 5.91 | 53 | 53.7 | 53.3 | 245 | 147 | 6.12 |
| 4 | 62.9 | 66.4 | 250 | 143.9 | 6.22 | 54 | 62.9 | 51 | 245 | 145.7 | 6.22 |
| 5 | 62.5 | 65.6 | 250 | 142.4 | 6.26 | 55 | 62.5 | 50.9 | 245 | 142.5 | 6.21 |
| 6 | 61.7 | 65.7 | 250 | 143.5 | 5.86 | 56 | 61.4 | 61.2 | 245 | 140.5 | 6.22 |
| 7 | 62.4 | 65.7 | 250 | 142.3 | 6.24 | 57 | 65.8 | 51 | 245 | 145 | 6.26 |
| 8 | 61.2 | 65.6 | 250 | 142.7 | 6.23 | 58 | 68.9 | 50.1 | 245 | 141.1 | 6.28 |
| 9 | 61.2 | 66.1 | 250 | 141.2 | 6.33 | 59 | 62.2 | 64.1 | 245 | 145 | 6.25 |
| 10 | 60.1 | 50.6 | 238 | 141.6 | 6.25 | 60 | 61.2 | 61.4 | 245 | 146.8 | 6.13 |
| 11 | 62.9 | 49.8 | 238 | 142.7 | 6.26 | 61 | 59 | 61.5 | 245 | 147.8 | 6 |
| 12 | 63.5 | 48.9 | 238 | 143.3 | 6.07 | 62 | 54.4 | 63.1 | 245 | 147.5 | 5.98 |
| 13 | 61.6 | 49.9 | 238 | 148 | 6.22 | 63 | 55.4 | 55.9 | 245 | 145 | 6.2 |
| 14 | 63.7 | 49.8 | 238 | 153.7 | 6 | 64 | 54.4 | 54.5 | 245 | 146.8 | 6.05 |
| 15 | 60.2 | 51 | 238 | 160.2 | 5.36 | 65 | 57.2 | 54.2 | 245 | 146.8 | 6.12 |
| 16 | 62.4 | 50.3 | 238 | 152.4 | 6 | 66 | 59.7 | 54.1 | 245 | 144.1 | 6.29 |
| 17 | 63.8 | 50.8 | 238 | 153.6 | 6.06 | 67 | 46.8 | 54.2 | 245 | 146.1 | 6.19 |
| 18 | 58.7 | 51.9 | 238 | 148.1 | 5.15 | 68 | 55.2 | 54.3 | 240 | 147 | 6.14 |
| 19 | 63.3 | 48 | 238 | 156.2 | 5.7 | 69 | 57.6 | 52 | 240 | 153.5 | 5.95 |
| 20 | 63.8 | 48 | 245 | 148.5 | 6.2 | 70 | 59.5 | 51.9 | 240 | 146.4 | 6.1 |
| 21 | 64.8 | 47.8 | 245 | 146.4 | 5.36 | 71 | 55.1 | 53.2 | 240 | 155.7 | 5.52 |
| 22 | 61.7 | 48.1 | 245 | 144 | 6.22 | 72 | 57.5 | 53.2 | 240 | 146.7 | 6.1 |
| 23 | 59.8 | 48.6 | 245 | 155 | 5.85 | 73 | 56.6 | 52.9 | 240 | 156.1 | 5.74 |
| 24 | 63.4 | 47.6 | 245 | 145.2 | 5.99 | 74 | 58.8 | 52.6 | 245 | 148.6 | 6.05 |
| 25 | 61.3 | 51 | 245 | 155.4 | 5.73 | 75 | 59.2 | 51.9 | 245 | 153.7 | 5.95 |
| 26 | 62.9 | 53 | 245 | 153.2 | 6 | 76 | 57.8 | 51.8 | 245 | 144.6 | 6.21 |
| 27 | 62.1 | 51 | 245 | 156.5 | 5.27 | 77 | 62.8 | 50.9 | 245 | 142.2 | 6.18 |
| 28 | 63.2 | 50.1 | 245 | 151.2 | 6.01 | 78 | 59 | 51.1 | 245 | 148.9 | 6.09 |
| 29 | 59.2 | 55 | 245 | 154.2 | 5.9 | 79 | 58.9 | 51 | 245 | 153.6 | 5.95 |
| 30 | 55.8 | 54.3 | 245 | 153.1 | 5.75 | 80 | 60.6 | 52.8 | 245 | 153.1 | 6 |
| 31 | 61 | 50.4 | 245 | 152.1 | 5.86 | 81 | 63.9 | 52.7 | 245 | 127.6 | 6.2 |
| 32 | 59 | 50.8 | 245 | 150.6 | 6.12 | 82 | 55.5 | 71.7 | 245 | 151.3 | 5.73 |
| 33 | 62.7 | 50.9 | 245 | 149.2 | 6.25 | 83 | 56.7 | 57.3 | 245 | 149.7 | 5.9 |
| 34 | 62 | 50.7 | 245 | 149.8 | 6 | 84 | 51.9 | 54.9 | 245 | 147.3 | 6.14 |
| 35 | 62.7 | 49.9 | 245 | 158.3 | 5.72 | 85 | 55.1 | 54.1 | 245 | 145.5 | 6.17 |
| 36 | 58.3 | 49.4 | 245 | 139.2 | 6.2 | 86 | 53.6 | 61.1 | 245 | 134.7 | 6.19 |
| 37 | 58.4 | 48.5 | 245 | 150.5 | 6.1 | 87 | 50 | 58.7 | 245 | 153.3 | 5.95 |
| 38 | 60.7 | 48.9 | 245 | 155.3 | 5.41 | 88 | 54.6 | 66.9 | 245 | 135.1 | 6.25 |
| 39 | 57.1 | 49.5 | 245 | 143.1 | 6.24 | 89 | 56.8 | 69.9 | 245 | 158.1 | 5.7 |
| 40 | 60.8 | 48.1 | 245 | 138.3 | 6.22 | 90 | 51.2 | 72.5 | 245 | 158.7 | 5.7 |
| 41 | 61.4 | 48.6 | 245 | 134.5 | 6.58 | 91 | 53 | 72.5 | 248 | 148.9 | 6 |
| 42 | 61.1 | 48.1 | 245 | 153.7 | 6.01 | 92 | 53.4 | 72.6 | 248 | 146.7 | 6.05 |
| 43 | 59.8 | 48.1 | 245 | 143.1 | 6.22 | 93 | 55.3 | 61.1 | 248 | 147.9 | 5.95 |
| 44 | 57 | 67 | 245 | 142.1 | 6.2 | 94 | 58.9 | 61 | 248 | 145.6 | 6.2 |
| 45 | 55 | 66.7 | 245 | 144.2 | 6.19 | 95 | 59 | 60.9 | 248 | 133.6 | 6.24 |
| 46 | 60.1 | 62.1 | 245 | 143 | 5.81 | 96 | 51.7 | 54.3 | 248 | 142.2 | 6.24 |
| 47 | 63.4 | 63.4 | 245 | 144.4 | 6.28 | 97 | 58 | 51.2 | 248 | 131.3 | 6.23 |
| 48 | 63.2 | 59.2 | 245 | 139.1 | 6.2 | 98 | 51.5 | 50.4 | 248 | 134.5 | 6.25 |
| 49 | 63.2 | 61 | 245 | 160.1 | 5.54 | 99 | 55.2 | 51.1 | 248 | 153.4 | 5.7 |
| 50 | 55.9 | 53.3 | 245 | 147.2 | 6 | 100 | 56.5 | 51 | 248 | 135.1 | 6.25 |

*R* = roller mill current (Ampere), *B* = blower air flow current (Ampere), *C* = classifier speed (rpm)
*T* = temperature (C), *CW* = actual combined water

April 2015

| Data | $R$ | $B$ | $C$ | $T$ | $CW$ | Data | $R$ | $B$ | $C$ | $T$ | $CW$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 60.9 | 52.7 | 245 | 143.6 | 6.2 | 51 | 54.4 | 51.3 | 250 | 147.9 | 5.98 |
| 2 | 52.2 | 54.3 | 245 | 141.9 | 6.25 | 52 | 52.2 | 51.3 | 250 | 144.9 | 6.18 |
| 3 | 54.1 | 53.1 | 245 | 151.5 | 5.55 | 53 | 52.7 | 51.7 | 250 | 143.2 | 6.23 |
| 4 | 58.4 | 53.6 | 245 | 131.5 | 6.18 | 54 | 62.2 | 50 | 250 | 155 | 5.83 |
| 5 | 56.8 | 53.7 | 240 | 141.5 | 6.22 | 55 | 65.5 | 49.9 | 250 | 141.8 | 6.2 |
| 6 | 65.5 | 52.4 | 240 | 147.9 | 6.2 | 56 | 68.2 | 50.9 | 250 | 142.9 | 6.22 |
| 7 | 52.8 | 54.8 | 240 | 141.9 | 6.18 | 57 | 55.9 | 50.9 | 250 | 133.4 | 6.24 |
| 8 | 53.9 | 55.2 | 230 | 155.7 | 5.72 | 58 | 58.4 | 50.5 | 250 | 135.7 | 6.2 |
| 9 | 63.2 | 53.1 | 230 | 145.6 | 6.2 | 59 | 59.2 | 50.6 | 250 | 138.1 | 6.24 |
| 10 | 64 | 53 | 230 | 136.9 | 6.25 | 60 | 59.6 | 50.1 | 250 | 136 | 6.23 |
| 11 | 61.2 | 53.3 | 230 | 141.1 | 6.2 | 61 | 55.8 | 50.8 | 250 | 150.9 | 5.81 |
| 12 | 52.1 | 54.9 | 230 | 153.7 | 5.89 | 62 | 55.6 | 51.1 | 250 | 160.2 | 5.77 |
| 13 | 45.8 | 55.8 | 230 | 143.5 | 6.21 | 63 | 61.9 | 54.5 | 250 | 162.6 | 5.74 |
| 14 | 53.9 | 53.4 | 231 | 137.4 | 6.2 | 64 | 61.9 | 53.6 | 250 | 147.8 | 6 |
| 15 | 55.2 | 53.4 | 231 | 160.3 | 5.56 | 65 | 57.8 | 53.7 | 250 | 135.2 | 6.18 |
| 16 | 54.8 | 53.3 | 231 | 149.5 | 5.9 | 66 | 60.3 | 52.4 | 250 | 145.1 | 6.15 |
| 17 | 58.3 | 52.4 | 231 | 143.5 | 6.2 | 67 | 58.5 | 52.4 | 250 | 160.4 | 5.72 |
| 18 | 55.4 | 52.9 | 231 | 143 | 6.17 | 68 | 60.5 | 50.1 | 250 | 143.8 | 6.2 |
| 19 | 54.2 | 52.7 | 231 | 153.5 | 5.55 | 69 | 55.9 | 51.9 | 250 | 145.7 | 6.14 |
| 20 | 55.4 | 52.9 | 231 | 140.6 | 6.25 | 70 | 56.8 | 51.9 | 250 | 137.2 | 6.23 |
| 21 | 46.5 | 53.4 | 231 | 145 | 6.19 | 71 | 52.9 | 52.9 | 250 | 139.7 | 6.21 |
| 22 | 52.7 | 63 | 250 | 154.1 | 5.34 | 72 | 53.9 | 52.7 | 250 | 144 | 6.17 |
| 23 | 58.6 | 60 | 250 | 147 | 6.04 | 73 | 53.6 | 52.2 | 250 | 142.8 | 6.2 |
| 24 | 55.7 | 59.4 | 250 | 154.1 | 5.73 | 74 | 65.8 | 49.7 | 250 | 144 | 6.25 |
| 25 | 56 | 59 | 250 | 156.6 | 5.78 | 75 | 56.3 | 51 | 250 | 143.3 | 6.21 |
| 26 | 66.6 | 59.1 | 250 | 152.1 | 5.91 | 76 | 52.3 | 52.8 | 250 | 156.8 | 5.22 |
| 27 | 60.7 | 53.3 | 250 | 140.7 | 6.18 | 77 | 52.5 | 52.1 | 250 | 142.8 | 6.19 |
| 28 | 56.2 | 55.2 | 250 | 142 | 6.18 | 78 | 50.1 | 51.3 | 250 | 140.9 | 6.21 |
| 29 | 60.4 | 53.4 | 250 | 152.3 | 6.02 | 79 | 60.5 | 49.8 | 250 | 144.2 | 6.25 |
| 30 | 56.4 | 53.7 | 250 | 152.4 | 5.85 | 80 | 53 | 51.4 | 250 | 143.3 | 6.19 |
| 31 | 56.6 | 53.7 | 250 | 140.4 | 6.19 | 81 | 53.4 | 51.6 | 250 | 144.9 | 6.17 |
| 32 | 56.1 | 51.6 | 250 | 150.8 | 5.8 | 82 | 56.8 | 51.1 | 245 | 144.6 | 6.2 |
| 33 | 55.9 | 51.3 | 250 | 146.3 | 6.15 | 83 | 60.8 | 50.5 | 245 | 144 | 6.21 |
| 34 | 56.8 | 51.5 | 250 | 151.5 | 5.9 | 84 | 54.9 | 51.1 | 245 | 143.7 | 6.2 |
| 35 | 56 | 51 | 250 | 147.6 | 6 | 85 | 53.4 | 51.4 | 245 | 142.4 | 6.19 |
| 36 | 56.6 | 51.9 | 250 | 153.3 | 5.88 | 86 | 56.8 | 51.2 | 245 | 141.7 | 6.25 |
| 37 | 56.4 | 51.2 | 250 | 159.1 | 5.72 | 87 | 54.1 | 52.3 | 245 | 139.3 | 6.17 |
| 38 | 55 | 51.2 | 250 | 154.5 | 5.66 | 88 | 58.5 | 50.1 | 245 | 140.5 | 6.17 |
| 39 | 58.8 | 50.2 | 250 | 141.5 | 6.23 | 89 | 51.1 | 52.6 | 245 | 139 | 6.2 |
| 40 | 59.1 | 46.5 | 250 | 149.4 | 6.09 | 90 | 54.8 | 51.1 | 245 | 141.2 | 6.25 |
| 41 | 55.6 | 51 | 250 | 153.2 | 5.69 | 91 | 52.7 | 52.1 | 245 | 149.8 | 6.01 |
| 42 | 55 | 50.3 | 250 | 148.2 | 5.96 | 92 | 53.9 | 51.5 | 245 | 141.1 | 6.16 |
| 43 | 55 | 52.4 | 250 | 147.4 | 6.04 | 93 | 62.3 | 49 | 245 | 149.4 | 6.2 |
| 44 | 52.5 | 51.1 | 250 | 153.6 | 5.35 | 94 | 61.1 | 50.2 | 245 | 145 | 6.25 |
| 45 | 59.5 | 49.9 | 250 | 141 | 6.21 | 95 | 57.7 | 51.1 | 245 | 139.5 | 6.22 |
| 46 | 63.5 | 49.7 | 250 | 155.5 | 5.75 | 96 | 52.6 | 52.5 | 235 | 151.6 | 5.65 |
| 47 | 61.8 | 49.8 | 250 | 151.1 | 6.16 | 97 | 50.4 | 52.6 | 235 | 147.2 | 6.22 |
| 48 | 52.9 | 50.5 | 250 | 139 | 6.25 | 98 | 49.9 | 53.8 | 235 | 158.4 | 5.38 |
| 49 | 57.6 | 51.1 | 250 | 149.7 | 5.95 | 99 | 56.7 | 52.8 | 235 | 154 | 5.9 |
| 50 | 58.1 | 50.3 | 250 | 153.1 | 6 | 100 | 50.1 | 52.8 | 235 | 148.1 | 6.22 |

$R$ = roller mill current (Ampere), $B$ = blower air flow current (Ampere), $C$ = classifier speed (rpm)
$T$ = temperature (C), $CW$ = actual combined water

May 2015

| Data | $R$ | $B$ | $C$ | $T$ | $CW$ | Data | $R$ | $B$ | $C$ | $T$ | $CW$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 51.1 | 52.3 | 235 | 153.6 | 5.42 | 51 | 55.2 | 52.8 | 250 | 152.4 | 5.27 |
| 2 | 51.8 | 52.2 | 235 | 148.9 | 6.15 | 52 | 58 | 52.2 | 250 | 152.3 | 5.96 |
| 3 | 53.1 | 51.5 | 235 | 148.8 | 6.02 | 53 | 57.7 | 52.2 | 250 | 150.7 | 6 |
| 4 | 56.3 | 58.2 | 255 | 143.3 | 6 | 54 | 57.2 | 52.1 | 250 | 152.2 | 5.92 |
| 5 | 57.4 | 56.5 | 260 | 155 | 5.36 | 55 | 57.5 | 52.1 | 250 | 150.7 | 5.99 |
| 6 | 60.1 | 54.5 | 260 | 143.9 | 6.2 | 56 | 54.6 | 53.3 | 250 | 153 | 5.54 |
| 7 | 56.1 | 55.4 | 255 | 155.6 | 5.6 | 57 | 55.3 | 52 | 250 | 154 | 5.72 |
| 8 | 56.6 | 54.9 | 255 | 148.5 | 5.95 | 58 | 57.7 | 52.6 | 250 | 156.6 | 5.77 |
| 9 | 56.7 | 54.7 | 255 | 149.4 | 5.81 | 59 | 63.8 | 51.4 | 250 | 156.2 | 5.75 |
| 10 | 56.4 | 54.7 | 250 | 151.9 | 5.82 | 60 | 55 | 53 | 250 | 152.4 | 5.82 |
| 11 | 58.5 | 54.8 | 250 | 150.6 | 5.9 | 61 | 57.1 | 52.6 | 250 | 153.1 | 5.92 |
| 12 | 55.4 | 55 | 250 | 152.3 | 5.72 | 62 | 55.1 | 71 | 250 | 148.7 | 5.9 |
| 13 | 55.6 | 53.7 | 250 | 149.8 | 5.77 | 63 | 52.9 | 71 | 250 | 147.5 | 5.47 |
| 14 | 55.7 | 54.6 | 250 | 156.3 | 5.78 | 64 | 58.3 | 55.7 | 250 | 144.2 | 6.17 |
| 15 | 59.7 | 53.5 | 250 | 153.5 | 5.89 | 65 | 54.5 | 50.2 | 250 | 147.7 | 5.96 |
| 16 | 56.6 | 54.8 | 250 | 155.6 | 5.7 | 66 | 57.6 | 57.7 | 250 | 153.2 | 5.73 |
| 17 | 58.8 | 53.8 | 250 | 153.3 | 5.89 | 67 | 57.6 | 59.3 | 250 | 151.9 | 5.87 |
| 18 | 58 | 53.8 | 250 | 151.3 | 5.87 | 68 | 59.6 | 56.1 | 250 | 154.2 | 5.89 |
| 19 | 56.2 | 55.3 | 250 | 152.7 | 5.84 | 69 | 53.9 | 57.3 | 250 | 152.2 | 5.75 |
| 20 | 56.8 | 54.3 | 250 | 153.3 | 5.89 | 70 | 62.8 | 54.3 | 250 | 154.6 | 5.8 |
| 21 | 60.1 | 53.9 | 250 | 151.3 | 5.86 | 71 | 50.6 | 60 | 250 | 154.6 | 5.2 |
| 22 | 63.7 | 52 | 250 | 152.1 | 6.03 | 72 | 53.8 | 61.9 | 250 | 150.5 | 5.83 |
| 23 | 55.7 | 53.3 | 250 | 153.6 | 5.75 | 73 | 60.1 | 56.4 | 250 | 151.8 | 5.95 |
| 24 | 56.5 | 53.4 | 250 | 154.6 | 6.16 | 74 | 53.9 | 58 | 250 | 147.3 | 6.02 |
| 25 | 55.5 | 53.3 | 250 | 150.7 | 5.75 | 75 | 51.7 | 58.7 | 250 | 147.4 | 5.77 |
| 26 | 61.9 | 52.9 | 250 | 149.6 | 6 | 76 | 50.6 | 58.9 | 250 | 148 | 6.04 |
| 27 | 58.5 | 53.1 | 250 | 149.7 | 5.91 | 77 | 55.4 | 59.6 | 250 | 152.6 | 5.67 |
| 28 | 60 | 52.7 | 250 | 153 | 5.96 | 78 | 53.3 | 59.9 | 250 | 152 | 5.81 |
| 29 | 57.6 | 52.8 | 250 | 152.4 | 5.97 | 79 | 61.7 | 53.9 | 250 | 149.2 | 5.96 |
| 30 | 57.5 | 52.8 | 250 | 152.8 | 6.04 | 80 | 56.4 | 54.6 | 250 | 150.2 | 5.84 |
| 31 | 57.1 | 52.7 | 250 | 151.4 | 5.92 | 81 | 57.8 | 54.1 | 250 | 145.9 | 5.35 |
| 32 | 59.1 | 52.1 | 250 | 151.1 | 6.02 | 82 | 56.3 | 53.7 | 250 | 155.1 | 5.75 |
| 33 | 59.1 | 52.4 | 250 | 155.1 | 6.08 | 83 | 56.4 | 55 | 250 | 156 | 5.72 |
| 34 | 58.5 | 52.8 | 250 | 152.8 | 6 | 84 | 56.7 | 56.7 | 250 | 148.9 | 5.93 |
| 35 | 55.1 | 52.8 | 250 | 152.6 | 5.63 | 85 | 62.3 | 57.9 | 250 | 116.1 | 6.23 |
| 36 | 57 | 52.7 | 250 | 150.3 | 5.66 | 86 | 56.8 | 57.3 | 250 | 125.4 | 6.22 |
| 37 | 50.5 | 52 | 250 | 151.1 | 5.58 | 87 | 62.9 | 57 | 255 | 145.9 | 6.1 |
| 38 | 59.5 | 51.9 | 250 | 149.1 | 6.1 | 88 | 59.9 | 56.6 | 255 | 151 | 5.45 |
| 39 | 57 | 52.2 | 250 | 151.7 | 5.38 | 89 | 60.9 | 55.5 | 255 | 140 | 6.24 |
| 40 | 58.2 | 52 | 250 | 147.1 | 6 | 90 | 61.9 | 54.5 | 255 | 147.7 | 6.05 |
| 41 | 56.6 | 52 | 250 | 149.1 | 6 | 91 | 57.8 | 55.1 | 255 | 143.7 | 6.23 |
| 42 | 58.8 | 51.8 | 250 | 151.2 | 6.14 | 92 | 58 | 55 | 255 | 147.6 | 6.06 |
| 43 | 58.8 | 52.2 | 250 | 148.2 | 6.04 | 93 | 54.5 | 56.2 | 255 | 151.4 | 5.54 |
| 44 | 56.8 | 52.1 | 250 | 153.9 | 5.9 | 94 | 54.5 | 56.2 | 255 | 149.8 | 5.85 |
| 45 | 62 | 51.9 | 250 | 152.9 | 5.67 | 95 | 56.5 | 54.8 | 255 | 152.7 | 5.78 |
| 46 | 59.6 | 51.2 | 250 | 151.4 | 6.1 | 96 | 61.9 | 54.9 | 255 | 150.1 | 5.75 |
| 47 | 57.3 | 52.3 | 250 | 155 | 5.88 | 97 | 53.8 | 56.3 | 255 | 152.2 | 5.5 |
| 48 | 58 | 50.9 | 250 | 154 | 6.13 | 98 | 46.1 | 56.9 | 255 | 152.7 | 5.58 |
| 49 | 60.3 | 51 | 250 | 151.9 | 6.06 | 99 | 57.1 | 54.5 | 255 | 156.3 | 5.75 |
| 50 | 59.6 | 51.2 | 250 | 150 | 6.12 | 100 | 57.7 | 54.6 | 255 | 151.3 | 5.86 |

$R$ = roller mill current (Ampere), $B$ = blower air flow current (Ampere), $C$ = classifier speed (rpm)

$T$ = temperature (C), $CW$ = actual combined water

# APPENDIX B
## MATLAB program source codes

1. FIS model source codes for process control application.

```
[System]
Name='Process Control'
Type='mamdani'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=81
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='RollerMill'
Range=[26.9 70]
NumMFs=3
MF1='L':'trapmf',[1 18.6 51.4 56.1]
MF2='M':'trimf',[51.4 56.1 60.8]
MF3='H':'trapmf',[56.1 60.8 72.72 86.54]

[Input2]
Name='Blower'
Range=[36.6 72.6]
NumMFs=3
MF1='L':'trapmf',[23.64 35.16 49.8 54.8]
MF2='H':'trapmf',[54.8 59.8 74.22 85.74]
MF3='M':'trimf',[49.8 54.8 59.8]

[Input3]
Name='Classifier'
Range=[230 265]
NumMFs=3
MF1='L':'trapmf',[212.1 223.7 244 250.6]
MF2='H':'trapmf',[250.6 257.2 272.8 284.5]
MF3='M':'trimf',[244 250.6 257.2]

[Input4]
Name='Temp'
Range=[116.1 165.7]
NumMFs=3
MF1='L':'trapmf',[98.08 114.4 142.5 148.3]
MF2='M':'trimf',[142.5 148.3 154]
MF3='H':'trapmf',[148.3 154 167.4 183.9]

[Output1]
Name='CW'
Range=[4.5 6.5]
NumMFs=5
MF1='L':'trapmf',[3.39 4.04 5.2 5.69]
```

MF2='M':'trimf',[5.2 5.69 6.2]
MF3='H':'trapmf',[5.69 6.2 6.6 7]
MF4='VL':'trapmf',[3.32 3.87 4.8 5.201]
MF5='VH':'trapmf',[6.195 6.6 6.9 7.49]

[Rules]
1 1 1 1, 1 (1) : 1
1 1 1 2, 1 (1) : 1
1 1 1 3, 5 (1) : 1
1 1 3 1, 1 (1) : 1
1 1 3 2, 1 (1) : 1
1 1 3 3, 3 (1) : 1
1 1 2 1, 1 (1) : 1
1 1 2 2, 2 (1) : 1
1 1 2 3, 3 (1) : 1
1 3 1 1, 1 (1) : 1
1 3 1 2, 1 (1) : 1
1 3 1 3, 2 (1) : 1
1 3 3 1, 1 (1) : 1
1 3 3 2, 2 (1) : 1
1 3 3 3, 2 (1) : 1
1 3 2 1, 1 (1) : 1
1 3 2 2, 2 (1) : 1
1 3 2 3, 2 (1) : 1
1 2 1 1, 4 (1) : 1
1 2 1 2, 1 (1) : 1
1 2 1 3, 2 (1) : 1
1 2 3 1, 1 (1) : 1
1 2 3 2, 2 (1) : 1
1 2 3 3, 3 (1) : 1
1 2 2 1, 1 (1) : 1
1 2 2 2, 1 (1) : 1
1 2 2 3, 2 (1) : 1
2 1 1 1, 1 (1) : 1
2 1 1 2, 1 (1) : 1
2 1 1 3, 2 (1) : 1
2 1 3 1, 1 (1) : 1
2 1 3 2, 2 (1) : 1
2 1 3 3, 2 (1) : 1
2 1 2 1, 1 (1) : 1
2 1 2 2, 2 (1) : 1
2 1 2 3, 2 (1) : 1
2 3 1 1, 1 (1) : 1
2 3 1 2, 2 (1) : 1
2 3 1 3, 2 (1) : 1
2 3 3 1, 1 (1) : 1
2 3 3 2, 2 (1) : 1
2 3 3 3, 2 (1) : 1
2 3 2 1, 1 (1) : 1
2 3 2 2, 2 (1) : 1
2 3 2 3, 2 (1) : 1
2 2 1 1, 1 (1) : 1

2 2 1 2, 2 (1) : 1
2 2 1 3, 2 (1) : 1
2 2 3 1, 1 (1) : 1
2 2 3 2, 2 (1) : 1
2 2 3 3, 2 (1) : 1
2 2 2 1, 2 (1) : 1
2 2 2 2, 2 (1) : 1
2 2 2 3, 3 (1) : 1
3 1 1 1, 4 (1) : 1
3 1 1 2, 1 (1) : 1
3 1 1 3, 2 (1) : 1
3 1 3 1, 1 (1) : 1
3 1 3 2, 1 (1) : 1
3 1 3 3, 2 (1) : 1
3 1 2 1, 4 (1) : 1
3 1 2 2, 1 (1) : 1
3 1 2 3, 2 (1) : 1
3 3 1 1, 4 (1) : 1
3 3 1 2, 1 (1) : 1
3 3 1 3, 2 (1) : 1
3 3 3 1, 1 (1) : 1
3 3 3 2, 2 (1) : 1
3 3 3 3, 2 (1) : 1
3 3 2 1, 1 (1) : 1
3 3 2 2, 2 (1) : 1
3 3 2 3, 2 (1) : 1
3 2 1 1, 1 (1) : 1
3 2 1 2, 2 (1) : 1
3 2 1 3, 2 (1) : 1
3 2 3 1, 1 (1) : 1
3 2 3 2, 2 (1) : 1
3 2 3 3, 2 (1) : 1
3 2 2 1, 4 (1) : 1
3 2 2 2, 2 (1) : 1
3 2 2 3, 3 (1) : 1

2. ANFIS model for process control application.
    2.1 ANFIS_Trap model source codes

[System]
Name='PC_Trap'
Type='sugeno'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=81
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

```
[Input1]
Name='RollerMill'
Range=[26.9 64.8]
NumMFs=3
MF1='L':'trapmf',[4.125 19.6 50.12 55.61]
MF2='H':'trapmf',[55.61 61.1 70.3 82.4]
MF3='M':'trimf',[50.12 55.61 61.1]

[Input2]
Name='Blower'
Range=[47.6 71.5]
NumMFs=3
MF1='L':'trapmf',[34.2 42.5 49.96 55.09]
MF2='H':'trapmf',[55.09 60.22 75 80]
MF3='M':'trimf',[49.96 55.09 60.22]

[Input3]
Name='Classifier'
Range=[238 260]
NumMFs=3
MF1='L':'trapmf',[226.7 234 246 251.2]
MF2='H':'trapmf',[251.2 256.5 264.9 272.3]
MF3='M':'trimf',[246 251.2 256.5]

[Input4]
Name='Temp'
Range=[132 160.2]
NumMFs=3
MF1='L':'trapmf',[121 128 146.1 150.1]
MF2='M':'trimf',[146.1 150.1 154]
MF3='H':'trapmf',[150.1 154 160.3 169.5]

[Output1]
Name='CW'
Range=[0 1]
NumMFs=81
MF1='o1':'constant',[6.076]
MF2='o2':'constant',[6.084]
MF3='o3':'constant',[4.85]
MF4='o4':'constant',[6.092]
MF5='o5':'constant',[5.45]
MF6='o6':'constant',[5.44]
MF7='o7':'constant',[6.35]
MF8='o8':'constant',[5.465]
MF9='o9':'constant',[5.31]
MF10='o10':'constant',[6.1]
MF11='o11':'constant',[6.108]
MF12='o12':'constant',[5.48]
MF13='o13':'constant',[6.116]
MF14='o14':'constant',[5.495]
MF15='o15':'constant',[5.51]
MF16='o16':'constant',[6.068]
```

```
MF17='o17':'constant',[5.525]
MF18='o18':'constant',[5.54]
MF19='o19':'constant',[6.29]
MF20='o20':'constant',[6.124]
MF21='o21':'constant',[5.555]
MF22='o22':'constant',[6.132]
MF23='o23':'constant',[5.57]
MF24='o24':'constant',[5.18]
MF25='o25':'constant',[6.06]
MF26='o26':'constant',[6.14]
MF27='o27':'constant',[5.408]
MF28='o28':'constant',[6.148]
MF29='o29':'constant',[5.6]
MF30='o30':'constant',[5.615]
MF31='o31':'constant',[6.156]
MF32='o32':'constant',[5.63]
MF33='o33':'constant',[5.645]
MF34='o34':'constant',[6.164]
MF35='o35':'constant',[5.66]
MF36='o36':'constant',[5.675]
MF37='o37':'constant',[6.172]
MF38='o38':'constant',[5.69]
MF39='o39':'constant',[5.59]
MF40='o40':'constant',[6.18]
MF41='o41':'constant',[5.72]
MF42='o42':'constant',[5.735]
MF43='o43':'constant',[6.188]
MF44='o44':'constant',[5.75]
MF45='o45':'constant',[5.765]
MF46='o46':'constant',[6.196]
MF47='o47':'constant',[5.78]
MF48='o48':'constant',[5.795]
MF49='o49':'constant',[6.204]
MF50='o50':'constant',[5.81]
MF51='o51':'constant',[5.825]
MF52='o52':'constant',[5.84]
MF53='o53':'constant',[5.855]
MF54='o54':'constant',[5.05]
MF55='o55':'constant',[6.41]
MF56='o56':'constant',[6.26]
MF57='o57':'constant',[5.87]
MF58='o58':'constant',[6.268]
MF59='o59':'constant',[6.252]
MF60='o60':'constant',[5.885]
MF61='o61':'constant',[6.59]
MF62='o62':'constant',[6.276]
MF63='o63':'constant',[5.9]
MF64='o64':'constant',[6.53]
MF65='o65':'constant',[6.244]
MF66='o66':'constant',[5.915]
MF67='o67':'constant',[6.212]
MF68='o68':'constant',[5.93]
```

MF69='o69':'constant',[5.945]
MF70='o70':'constant',[6.228]
MF71='o71':'constant',[5.96]
MF72='o72':'constant',[5.975]
MF73='o73':'constant',[6.22]
MF74='o74':'constant',[5.99]
MF75='o75':'constant',[6.005]
MF76='o76':'constant',[6.236]
MF77='o77':'constant',[6.02]
MF78='o78':'constant',[6.035]
MF79='o79':'constant',[6.47]
MF80='o80':'constant',[6.05]
MF81='o81':'constant',[4.92]

[Rules]
1 1 1 1, 1 (1) : 1
1 1 1 2, 2 (1) : 1
1 1 1 3, 3 (1) : 1
1 1 3 1, 4 (1) : 1
1 1 3 2, 5 (1) : 1
1 1 3 3, 6 (1) : 1
1 1 2 1, 7 (1) : 1
1 1 2 2, 8 (1) : 1
1 1 2 3, 9 (1) : 1
1 3 1 1, 10 (1) : 1
1 3 1 2, 11 (1) : 1
1 3 1 3, 12 (1) : 1
1 3 3 1, 13 (1) : 1
1 3 3 2, 14 (1) : 1
1 3 3 3, 15 (1) : 1
1 3 2 1, 16 (1) : 1
1 3 2 2, 17 (1) : 1
1 3 2 3, 18 (1) : 1
1 2 1 1, 19 (1) : 1
1 2 1 2, 20 (1) : 1
1 2 1 3, 21 (1) : 1
1 2 3 1, 22 (1) : 1
1 2 3 2, 23 (1) : 1
1 2 3 3, 24 (1) : 1
1 2 2 1, 25 (1) : 1
1 2 2 2, 26 (1) : 1
1 2 2 3, 27 (1) : 1
3 1 1 1, 28 (1) : 1
3 1 1 2, 29 (1) : 1
3 1 1 3, 30 (1) : 1
3 1 3 1, 31 (1) : 1
3 1 3 2, 32 (1) : 1
3 1 3 3, 33 (1) : 1
3 1 2 1, 34 (1) : 1
3 1 2 2, 35 (1) : 1
3 1 2 3, 36 (1) : 1
3 3 1 1, 37 (1) : 1

```
3 3 1 2, 38 (1) : 1
3 3 1 3, 39 (1) : 1
3 3 3 1, 40 (1) : 1
3 3 3 2, 41 (1) : 1
3 3 3 3, 42 (1) : 1
3 3 2 1, 43 (1) : 1
3 3 2 2, 44 (1) : 1
3 3 2 3, 45 (1) : 1
3 2 1 1, 46 (1) : 1
3 2 1 2, 47 (1) : 1
3 2 1 3, 48 (1) : 1
3 2 3 1, 49 (1) : 1
3 2 3 2, 50 (1) : 1
3 2 3 3, 51 (1) : 1
3 2 2 1, 52 (1) : 1
3 2 2 2, 53 (1) : 1
3 2 2 3, 54 (1) : 1
2 1 1 1, 55 (1) : 1
2 1 1 2, 56 (1) : 1
2 1 1 3, 57 (1) : 1
2 1 3 1, 58 (1) : 1
2 1 3 2, 59 (1) : 1
2 1 3 3, 60 (1) : 1
2 1 2 1, 61 (1) : 1
2 1 2 2, 62 (1) : 1
2 1 2 3, 63 (1) : 1
2 3 1 1, 64 (1) : 1
2 3 1 2, 65 (1) : 1
2 3 1 3, 66 (1) : 1
2 3 3 1, 67 (1) : 1
2 3 3 2, 68 (1) : 1
2 3 3 3, 69 (1) : 1
2 3 2 1, 70 (1) : 1
2 3 2 2, 71 (1) : 1
2 3 2 3, 72 (1) : 1
2 2 1 1, 73 (1) : 1
2 2 1 2, 74 (1) : 1
2 2 1 3, 75 (1) : 1
2 2 3 1, 76 (1) : 1
2 2 3 2, 77 (1) : 1
2 2 3 3, 78 (1) : 1
2 2 2 1, 79 (1) : 1
2 2 2 2, 80 (1) : 1
2 2 2 3, 81 (1) : 1
```

2.2 ANFIS_Gauss model source codes

```
[System]
Name='PC_Gauss'
Type='sugeno'
Version=2.0
NumInputs=4
```

```
NumOutputs=1
NumRules=81
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='RollerMill'
Range=[26.9 64.8]
NumMFs=3
MF1='L':'gaussmf',[19.11 34.36]
MF2='H':'gaussmf',[6.519 66.03]
MF3='M':'gaussmf',[2.331 55.61]

[Input2]
Name='Blower'
Range=[47.6 71.5]
NumMFs=3
MF1='L':'gaussmf',[6.558 46.07]
MF2='H':'gaussmf',[8.449 67.6]
MF3='M':'gaussmf',[2.179 55.09]

[Input3]
Name='Classifier'
Range=[238 260]
NumMFs=3
MF1='L':'gaussmf',[8.107 239.9]
MF2='H':'gaussmf',[5.907 260.8]
MF3='M':'gaussmf',[2.212 251.2]

[Input4]
Name='Temp'
Range=[132 160.2]
NumMFs=3
MF1='L':'gaussmf',[10.53 136.9]
MF2='M':'gaussmf',[1.694 150.1]
MF3='H':'gaussmf',[4.557 157.4]

[Output1]
Name='CW'
Range=[0 1]
NumMFs=81
MF1='o1':'constant',[6.076]
MF2='o2':'constant',[6.084]
MF3='o3':'constant',[4.85]
MF4='o4':'constant',[6.092]
MF5='o5':'constant',[5.45]
MF6='o6':'constant',[5.44]
MF7='o7':'constant',[6.35]
MF8='o8':'constant',[5.465]
```

MF9='o9':'constant',[5.31]
MF10='o10':'constant',[6.1]
MF11='o11':'constant',[6.108]
MF12='o12':'constant',[5.48]
MF13='o13':'constant',[6.116]
MF14='o14':'constant',[5.495]
MF15='o15':'constant',[5.51]
MF16='o16':'constant',[6.068]
MF17='o17':'constant',[5.525]
MF18='o18':'constant',[5.54]
MF19='o19':'constant',[6.29]
MF20='o20':'constant',[6.124]
MF21='o21':'constant',[5.555]
MF22='o22':'constant',[6.132]
MF23='o23':'constant',[5.57]
MF24='o24':'constant',[5.18]
MF25='o25':'constant',[6.06]
MF26='o26':'constant',[6.14]
MF27='o27':'constant',[5.408]
MF28='o28':'constant',[6.148]
MF29='o29':'constant',[5.6]
MF30='o30':'constant',[5.615]
MF31='o31':'constant',[6.156]
MF32='o32':'constant',[5.63]
MF33='o33':'constant',[5.645]
MF34='o34':'constant',[6.164]
MF35='o35':'constant',[5.66]
MF36='o36':'constant',[5.675]
MF37='o37':'constant',[6.172]
MF38='o38':'constant',[5.69]
MF39='o39':'constant',[5.59]
MF40='o40':'constant',[6.18]
MF41='o41':'constant',[5.72]
MF42='o42':'constant',[5.735]
MF43='o43':'constant',[6.188]
MF44='o44':'constant',[5.75]
MF45='o45':'constant',[5.765]
MF46='o46':'constant',[6.196]
MF47='o47':'constant',[5.78]
MF48='o48':'constant',[5.795]
MF49='o49':'constant',[6.204]
MF50='o50':'constant',[5.81]
MF51='o51':'constant',[5.825]
MF52='o52':'constant',[5.84]
MF53='o53':'constant',[5.855]
MF54='o54':'constant',[5.05]
MF55='o55':'constant',[6.41]
MF56='o56':'constant',[6.26]
MF57='o57':'constant',[5.87]
MF58='o58':'constant',[6.268]
MF59='o59':'constant',[6.252]
MF60='o60':'constant',[5.885]

```
MF61='o61':'constant',[6.59]
MF62='o62':'constant',[6.276]
MF63='o63':'constant',[5.9]
MF64='o64':'constant',[6.53]
MF65='o65':'constant',[6.244]
MF66='o66':'constant',[5.915]
MF67='o67':'constant',[6.212]
MF68='o68':'constant',[5.93]
MF69='o69':'constant',[5.945]
MF70='o70':'constant',[6.228]
MF71='o71':'constant',[5.96]
MF72='o72':'constant',[5.975]
MF73='o73':'constant',[6.22]
MF74='o74':'constant',[5.99]
MF75='o75':'constant',[6.005]
MF76='o76':'constant',[6.236]
MF77='o77':'constant',[6.02]
MF78='o78':'constant',[6.035]
MF79='o79':'constant',[6.47]
MF80='o80':'constant',[6.05]
MF81='o81':'constant',[4.92]

[Rules]
1 1 1 1, 1 (1) : 1
1 1 1 2, 2 (1) : 1
1 1 1 3, 3 (1) : 1
1 1 3 1, 4 (1) : 1
1 1 3 2, 5 (1) : 1
1 1 3 3, 6 (1) : 1
1 1 2 1, 7 (1) : 1
1 1 2 2, 8 (1) : 1
1 1 2 3, 9 (1) : 1
1 3 1 1, 10 (1) : 1
1 3 1 2, 11 (1) : 1
1 3 1 3, 12 (1) : 1
1 3 3 1, 13 (1) : 1
1 3 3 2, 14 (1) : 1
1 3 3 3, 15 (1) : 1
1 3 2 1, 16 (1) : 1
1 3 2 2, 17 (1) : 1
1 3 2 3, 18 (1) : 1
1 2 1 1, 19 (1) : 1
1 2 1 2, 20 (1) : 1
1 2 1 3, 21 (1) : 1
1 2 3 1, 22 (1) : 1
1 2 3 2, 23 (1) : 1
1 2 3 3, 24 (1) : 1
1 2 2 1, 25 (1) : 1
1 2 2 2, 26 (1) : 1
1 2 2 3, 27 (1) : 1
3 1 1 1, 28 (1) : 1
3 1 1 2, 29 (1) : 1
```

3 1 1 3, 30 (1) : 1
3 1 3 1, 31 (1) : 1
3 1 3 2, 32 (1) : 1
3 1 3 3, 33 (1) : 1
3 1 2 1, 34 (1) : 1
3 1 2 2, 35 (1) : 1
3 1 2 3, 36 (1) : 1
3 3 1 1, 37 (1) : 1
3 3 1 2, 38 (1) : 1
3 3 1 3, 39 (1) : 1
3 3 3 1, 40 (1) : 1
3 3 3 2, 41 (1) : 1
3 3 3 3, 42 (1) : 1
3 3 2 1, 43 (1) : 1
3 3 2 2, 44 (1) : 1
3 3 2 3, 45 (1) : 1
3 2 1 1, 46 (1) : 1
3 2 1 2, 47 (1) : 1
3 2 1 3, 48 (1) : 1
3 2 3 1, 49 (1) : 1
3 2 3 2, 50 (1) : 1
3 2 3 3, 51 (1) : 1
3 2 2 1, 52 (1) : 1
3 2 2 2, 53 (1) : 1
3 2 2 3, 54 (1) : 1
2 1 1 1, 55 (1) : 1
2 1 1 2, 56 (1) : 1
2 1 1 3, 57 (1) : 1
2 1 3 1, 58 (1) : 1
2 1 3 2, 59 (1) : 1
2 1 3 3, 60 (1) : 1
2 1 2 1, 61 (1) : 1
2 1 2 2, 62 (1) : 1
2 1 2 3, 63 (1) : 1
2 3 1 1, 64 (1) : 1
2 3 1 2, 65 (1) : 1
2 3 1 3, 66 (1) : 1
2 3 3 1, 67 (1) : 1
2 3 3 2, 68 (1) : 1
2 3 3 3, 69 (1) : 1
2 3 2 1, 70 (1) : 1
2 3 2 2, 71 (1) : 1
2 3 2 3, 72 (1) : 1
2 2 1 1, 73 (1) : 1
2 2 1 2, 74 (1) : 1
2 2 1 3, 75 (1) : 1
2 2 3 1, 76 (1) : 1
2 2 3 2, 77 (1) : 1
2 2 3 3, 78 (1) : 1
2 2 2 1, 79 (1) : 1
2 2 2 2, 80 (1) : 1
2 2 2 3, 81 (1) : 1

## 2.3 ANFIS_Bell model source codes

```
[System]
Name='PC_Bell'
Type='sugeno'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=81
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='RollerMill'
Range=[26.9 64.8]
NumMFs=3
MF1='L':'gbellmf',[22.5 7.269 34.36]
MF2='H':'gbellmf',[7.675 6.99 66.03]
MF3='M':'gbellmf',[2.745 2.5 55.61]

[Input2]
Name='Blower'
Range=[47.6 71.5]
NumMFs=3
MF1='L':'gbellmf',[7.721 4.652 46.07]
MF2='H':'gbellmf',[9.948 9.696 67.6]
MF3='M':'gbellmf',[2.565 2.5 55.09]

[Input3]
Name='Classifier'
Range=[238 260]
NumMFs=3
MF1='L':'gbellmf',[9.545 6.538 239.9]
MF2='H':'gbellmf',[6.955 6.561 260.8]
MF3='M':'gbellmf',[2.605 2.505 251.2]

[Input4]
Name='Temp'
Range=[132 160.2]
NumMFs=3
MF1='L':'gbellmf',[12.4 8.857 136.9]
MF2='M':'gbellmf',[1.995 2.494 150.1]
MF3='H':'gbellmf',[5.365 6.878 157.4]

[Output1]
Name='CW'
Range=[0 1]
NumMFs=81
MF1='o1':'constant',[6.076]
```

MF2='o2':'constant',[6.084]
MF3='o3':'constant',[4.85]
MF4='o4':'constant',[6.092]
MF5='o5':'constant',[5.45]
MF6='o6':'constant',[5.44]
MF7='o7':'constant',[6.35]
MF8='o8':'constant',[5.465]
MF9='o9':'constant',[5.31]
MF10='o10':'constant',[6.1]
MF11='o11':'constant',[6.108]
MF12='o12':'constant',[5.48]
MF13='o13':'constant',[6.116]
MF14='o14':'constant',[5.495]
MF15='o15':'constant',[5.51]
MF16='o16':'constant',[6.068]
MF17='o17':'constant',[5.525]
MF18='o18':'constant',[5.54]
MF19='o19':'constant',[6.29]
MF20='o20':'constant',[6.124]
MF21='o21':'constant',[5.555]
MF22='o22':'constant',[6.132]
MF23='o23':'constant',[5.57]
MF24='o24':'constant',[5.18]
MF25='o25':'constant',[6.06]
MF26='o26':'constant',[6.14]
MF27='o27':'constant',[5.408]
MF28='o28':'constant',[6.148]
MF29='o29':'constant',[5.6]
MF30='o30':'constant',[5.615]
MF31='o31':'constant',[6.156]
MF32='o32':'constant',[5.63]
MF33='o33':'constant',[5.645]
MF34='o34':'constant',[6.164]
MF35='o35':'constant',[5.66]
MF36='o36':'constant',[5.675]
MF37='o37':'constant',[6.172]
MF38='o38':'constant',[5.69]
MF39='o39':'constant',[5.59]
MF40='o40':'constant',[6.18]
MF41='o41':'constant',[5.72]
MF42='o42':'constant',[5.735]
MF43='o43':'constant',[6.188]
MF44='o44':'constant',[5.75]
MF45='o45':'constant',[5.765]
MF46='o46':'constant',[6.196]
MF47='o47':'constant',[5.78]
MF48='o48':'constant',[5.795]
MF49='o49':'constant',[6.204]
MF50='o50':'constant',[5.81]
MF51='o51':'constant',[5.825]
MF52='o52':'constant',[5.84]
MF53='o53':'constant',[5.855]

MF54='o54':'constant',[5.05]
MF55='o55':'constant',[6.41]
MF56='o56':'constant',[6.26]
MF57='o57':'constant',[5.87]
MF58='o58':'constant',[6.268]
MF59='o59':'constant',[6.252]
MF60='o60':'constant',[5.885]
MF61='o61':'constant',[6.59]
MF62='o62':'constant',[6.276]
MF63='o63':'constant',[5.9]
MF64='o64':'constant',[6.53]
MF65='o65':'constant',[6.244]
MF66='o66':'constant',[5.915]
MF67='o67':'constant',[6.212]
MF68='o68':'constant',[5.93]
MF69='o69':'constant',[5.945]
MF70='o70':'constant',[6.228]
MF71='o71':'constant',[5.96]
MF72='o72':'constant',[5.975]
MF73='o73':'constant',[6.22]
MF74='o74':'constant',[5.99]
MF75='o75':'constant',[6.005]
MF76='o76':'constant',[6.236]
MF77='o77':'constant',[6.02]
MF78='o78':'constant',[6.035]
MF79='o79':'constant',[6.47]
MF80='o80':'constant',[6.05]
MF81='o81':'constant',[4.92]

[Rules]
1 1 1 1, 1 (1) : 1
1 1 1 2, 2 (1) : 1
1 1 1 3, 3 (1) : 1
1 1 3 1, 4 (1) : 1
1 1 3 2, 5 (1) : 1
1 1 3 3, 6 (1) : 1
1 1 2 1, 7 (1) : 1
1 1 2 2, 8 (1) : 1
1 1 2 3, 9 (1) : 1
1 3 1 1, 10 (1) : 1
1 3 1 2, 11 (1) : 1
1 3 1 3, 12 (1) : 1
1 3 3 1, 13 (1) : 1
1 3 3 2, 14 (1) : 1
1 3 3 3, 15 (1) : 1
1 3 2 1, 16 (1) : 1
1 3 2 2, 17 (1) : 1
1 3 2 3, 18 (1) : 1
1 2 1 1, 19 (1) : 1
1 2 1 2, 20 (1) : 1
1 2 1 3, 21 (1) : 1
1 2 3 1, 22 (1) : 1

1 2 3 2, 23 (1) : 1
1 2 3 3, 24 (1) : 1
1 2 2 1, 25 (1) : 1
1 2 2 2, 26 (1) : 1
1 2 2 3, 27 (1) : 1
3 1 1 1, 28 (1) : 1
3 1 1 2, 29 (1) : 1
3 1 1 3, 30 (1) : 1
3 1 3 1, 31 (1) : 1
3 1 3 2, 32 (1) : 1
3 1 3 3, 33 (1) : 1
3 1 2 1, 34 (1) : 1
3 1 2 2, 35 (1) : 1
3 1 2 3, 36 (1) : 1
3 3 1 1, 37 (1) : 1
3 3 1 2, 38 (1) : 1
3 3 1 3, 39 (1) : 1
3 3 3 1, 40 (1) : 1
3 3 3 2, 41 (1) : 1
3 3 3 3, 42 (1) : 1
3 3 2 1, 43 (1) : 1
3 3 2 2, 44 (1) : 1
3 3 2 3, 45 (1) : 1
3 2 1 1, 46 (1) : 1
3 2 1 2, 47 (1) : 1
3 2 1 3, 48 (1) : 1
3 2 3 1, 49 (1) : 1
3 2 3 2, 50 (1) : 1
3 2 3 3, 51 (1) : 1
3 2 2 1, 52 (1) : 1
3 2 2 2, 53 (1) : 1
3 2 2 3, 54 (1) : 1
2 1 1 1, 55 (1) : 1
2 1 1 2, 56 (1) : 1
2 1 1 3, 57 (1) : 1
2 1 3 1, 58 (1) : 1
2 1 3 2, 59 (1) : 1
2 1 3 3, 60 (1) : 1
2 1 2 1, 61 (1) : 1
2 1 2 2, 62 (1) : 1
2 1 2 3, 63 (1) : 1
2 3 1 1, 64 (1) : 1
2 3 1 2, 65 (1) : 1
2 3 1 3, 66 (1) : 1
2 3 3 1, 67 (1) : 1
2 3 3 2, 68 (1) : 1
2 3 3 3, 69 (1) : 1
2 3 2 1, 70 (1) : 1
2 3 2 2, 71 (1) : 1
2 3 2 3, 72 (1) : 1
2 2 1 1, 73 (1) : 1
2 2 1 2, 74 (1) : 1

```
2 2 1 3, 75 (1) : 1
2 2 3 1, 76 (1) : 1
2 2 3 2, 77 (1) : 1
2 2 3 3, 78 (1) : 1
2 2 2 1, 79 (1) : 1
2 2 2 2, 80 (1) : 1
2 2 2 3, 81 (1) : 1
```

3. FIS model source codes for inventory control application.

```
[System]
Name='FIS'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Demand'
Range=[1083 3700]
NumMFs=3
MF1='Low':'trapmf',[-992.5 -10 2298 2453]
MF2='Medium':'trimf',[2298 2453 2608]
MF3='High':'trapmf',[2453 2608 3912 4000]

[Input2]
Name='Supply'
Range=[0 13070]
NumMFs=3
MF1='Low':'trapmf',[-4705 -522.8 3268 6535]
MF2='Medium':'trimf',[3267.5 6535 9802.5]
MF3='High':'trapmf',[6535 9802.5 13600 17800]

[Output1]
Name='OrderQuantity'
Range=[0 13070]
NumMFs=3
MF1='Low':'trapmf',[-4710 -523 2277 6535]
MF2='Medium':'trimf',[2277 6535 10793]
MF3='High':'trapmf',[6535 10793 13600 17800]

[Rules]
1 1, 2 (1) : 1
1 2, 1 (1) : 1
1 3, 2 (1) : 1
2 1, 1 (1) : 1
```

2 2, 2 (1) : 1
2 3, 3 (1) : 1
3 1, 2 (1) : 1
3 2, 3 (1) : 1
3 3, 3 (1) : 1

4. ANFIS model for inventory control application.
   4.1 ANFIS_Trap model source codes

```
[System]
Name='D1_Qtrap'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='Demand'
Range=[1083 3700]
NumMFs=3
MF1='Low':'trapmf',[-992.5 -10 1676 2452]
MF2='Medium':'trimf',[1676 2452 3228]
MF3='High':'trapmf',[2452 3228 3912 4000]

[Input2]
Name='Supply'
Range=[0 13070]
NumMFs=3
MF1='Low':'trapmf',[-4705 -522.8 3268 6535]
MF2='Medium':'trimf',[3268 6535 9803]
MF3='High':'trapmf',[6535 9803 13600 17800]

[Output1]
Name='OrderQuantity'
Range=[0 1]
NumMFs=9
MF1='o1':'constant',[0]
MF2='o2':'constant',[1634]
MF3='o3':'constant',[3268]
MF4='o4':'constant',[4901]
MF5='o5':'constant',[6535]
MF6='o6':'constant',[8169]
MF7='o7':'constant',[9803]
MF8='o8':'constant',[11436]
MF9='o9':'constant',[13070]
```

```
[Rules]
1 1, 1 (1) : 1
1 2, 2 (1) : 1
1 3, 4 (1) : 1
2 1, 3 (1) : 1
2 2, 5 (1) : 1
2 3, 7 (1) : 1
3 1, 6 (1) : 1
3 2, 8 (1) : 1
3 3, 9 (1) : 1
```

4.2 ANFIS_Gauss model source codes

```
[System]
Name='D1_QGauss'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='Demand'
Range=[1083 3700]
NumMFs=3
MF1='Low':'gaussmf',[776 1676]
MF2='Medium':'gaussmf',[776 2452]
MF3='High':'gaussmf',[776 3228]

[Input2]
Name='Supply'
Range=[0 13070]
NumMFs=3
MF1='Low':'gaussmf',[3914 2567]
MF2='Medium':'gaussmf',[3914 6481]
MF3='High':'gaussmf',[3914 10395]

[Output1]
Name='OrderQuantity'
Range=[0 1]
NumMFs=9
MF1='o1':'constant',[0]
MF2='o2':'constant',[1634]
MF3='o3':'constant',[3268]
MF4='o4':'constant',[4901]
MF5='o5':'constant',[6535]
MF6='o6':'constant',[8169]
```

```
MF7='o7':'constant',[9803]
MF8='o8':'constant',[11436]
MF9='o9':'constant',[13070]

[Rules]
1 1, 1 (1) : 1
1 2, 2 (1) : 1
1 3, 4 (1) : 1
2 1, 3 (1) : 1
2 2, 5 (1) : 1
2 3, 7 (1) : 1
3 1, 6 (1) : 1
3 2, 8 (1) : 1
3 3, 9 (1) : 1
```

4.3 ANFIS_Bell model source codes

```
[System]
Name='D1_QBell'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='wtaver'

[Input1]
Name='Demand'
Range=[1083 3700]
NumMFs=3
MF1='Low':'gbellmf',[913.7 3.278 1677]
MF2='Medium':'gbellmf',[913.7 3.28 2453]
MF3='High':'gbellmf',[913.7 3.278 3229]

[Input2]
Name='Supply'
Range=[0 13070]
NumMFs=3
MF1='Low':'gbellmf',[4608 3.278 3268]
MF2='Medium':'gbellmf',[4608 3.278 6535]
MF3='High':'gbellmf',[4608 3.278 9803]

[Output1]
Name='OrderQuantity'
Range=[0 1]
NumMFs=9
MF1='o1':'constant',[0]
MF2='o2':'constant',[1634]
```

```
MF3='o3':'constant',[3268]
MF4='o4':'constant',[4901]
MF5='o5':'constant',[6535]
MF6='o6':'constant',[8169]
MF7='o7':'constant',[9803]
MF8='o8':'constant',[11436]
MF9='o9':'constant',[13070]

[Rules]
1 1, 1 (1) : 1
1 2, 2 (1) : 1
1 3, 4 (1) : 1
2 1, 3 (1) : 1
2 2, 5 (1) : 1
2 3, 7 (1) : 1
3 1, 6 (1) : 1
3 2, 8 (1) : 1
3 3, 9 (1) : 1
```

# APPENDIX C
# Example method to input data and get output data by using MATLAB

FIS model for process control application by using MATLAB command prompt.

```
>> a=readfis('Process Control')

a =

           name: 'Process Control'
           type: 'mamdani'
      andMethod: 'min'
       orMethod: 'max'
   defuzzMethod: 'centroid'
      impMethod: 'min'
      aggMethod: 'max'
          input: [1x4 struct]
         output: [1x1 struct]
           rule: [1x81 struct]

>> evalfis([51.5	53.3	260	145.8
51.2	52.7	260	154.5
52.3	51.8	260	152.4
50.5	52.8	260	151
57.4	51	260	153.7
52.9	51.7	260	156.3
53.4	50.9	260	155
52	52	260	151
51.5	51.8	260	151.8
53.1	51.6	260	150
53.9	50.7	260	150.9
53	50.8	260	148.6
50.5	51.6	260	149.7
55.5	51.1	260	150.7
],a)

ans =

    5.3279
    5.8764
    5.9640
    5.8773
    5.6326
    5.9744
    5.9510
    5.9016
    5.9640
    5.8267
    5.8951
    5.7215
    5.8059
    5.7591
```

ANFIS_Bell model for process control application by using MATLAB command prompt.

```
>> b=readfis('PC_B1')

b =

           name: 'PC_B1'
           type: 'sugeno'
      andMethod: 'prod'
       orMethod: 'probor'
   defuzzMethod: 'wtaver'
      impMethod: 'prod'
      aggMethod: 'sum'
          input: [1x4 struct]
         output: [1x1 struct]
           rule: [1x81 struct]

>> evalfis([51.5	53.3	260	145.8
51.2	52.7	260	154.5
52.3	51.8	260	152.4
50.5	52.8	260	151
57.4	51	260	153.7
52.9	51.7	260	156.3
53.4	50.9	260	155
52	52	260	151
51.5	51.8	260	151.8
53.1	51.6	260	150
53.9	50.7	260	150.9
53	50.8	260	148.6
50.5	51.6	260	149.7
55.5	51.1	260	150.7
],b)

ans =

    5.9541
    5.6048
    5.5827
    5.5605
    5.9170
    5.4561
    5.8231
    5.6211
    5.5919
    5.6611
    5.6175
    5.8722
    5.8341
    5.7773
```

FIS model for inventory control application by using MATLAB command prompt.

```
>> a = readfis('FIS')

a =

          name: 'FIS'
          type: 'mamdani'
     andMethod: 'min'
      orMethod: 'max'
  defuzzMethod: 'centroid'
     impMethod: 'min'
     aggMethod: 'max'
         input: [1x2 struct]
        output: [1x1 struct]
          rule: [1x9 struct]

>> evalfis([2832   4407
1966    4468
2553    10584
3589    12338
2268    4284
1552    10802
2749    10985
1858    7212
3550    934
3037    5220
1262    11982
3700    6369
3461    5379
1422    11749
],a)

ans =

  1.0e+04 *

    0.7658
    0.5346
    1.0462
    1.0731
    0.5543
    0.6535
    1.0731
    0.3547
    0.6535
    0.8616
    0.6535
    1.0403
    0.8826
    0.6535
```

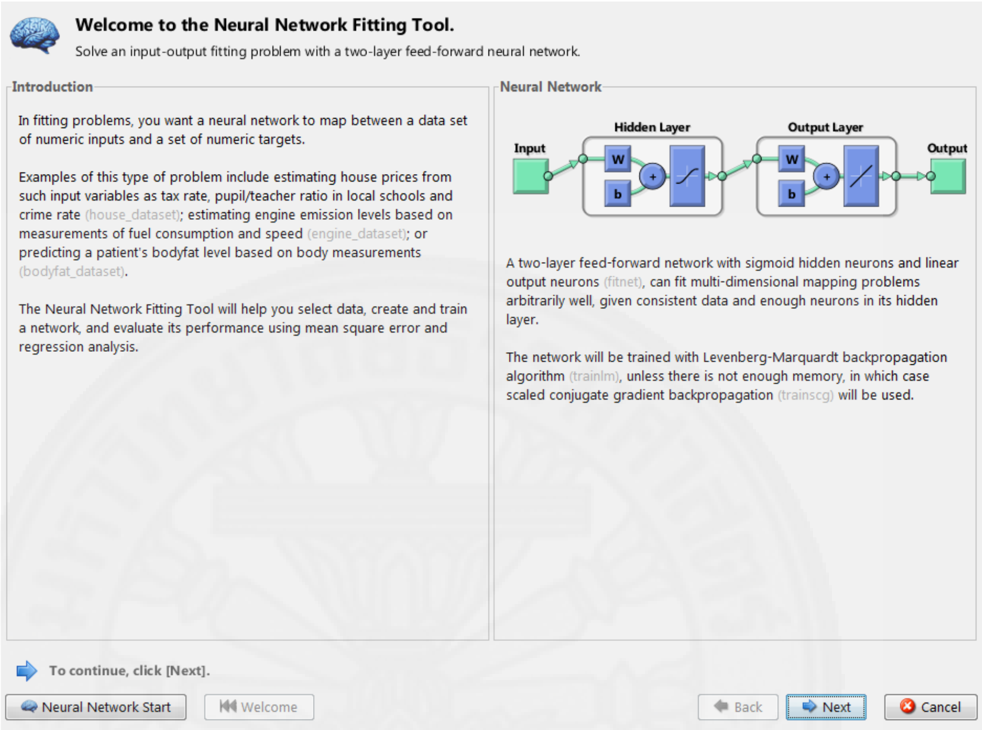
ANFIS_Gauss model for inventory control application by using MATLAB command prompt.

```
>> b=readfis('D1_QGauss_opt')

b =

          name: 'D1_QGauss_opt'
          type: 'sugeno'
     andMethod: 'prod'
      orMethod: 'probor'
   defuzzMethod: 'wtaver'
     impMethod: 'prod'
     aggMethod: 'sum'
         input: [1x2 struct]
        output: [1x1 struct]
          rule: [1x9 struct]

>> evalfis([2832   4407
1966    4468
2553    10584
3589    12338
2268    4284
1552    10802
2749    10985
1858    7212
3550    934
3037    5220
1262    11982
3700    6369
3461    5379
1422    11749
],b)

ans =

  1.0e+04 *

    0.7693
    0.5382
    1.0666
    1.0566
    0.4946
    0.6295
    1.0627
    0.3519
    0.6679
    0.8767
    0.6660
    1.0171
    0.8985
    0.6617
```

# APPENDIX D

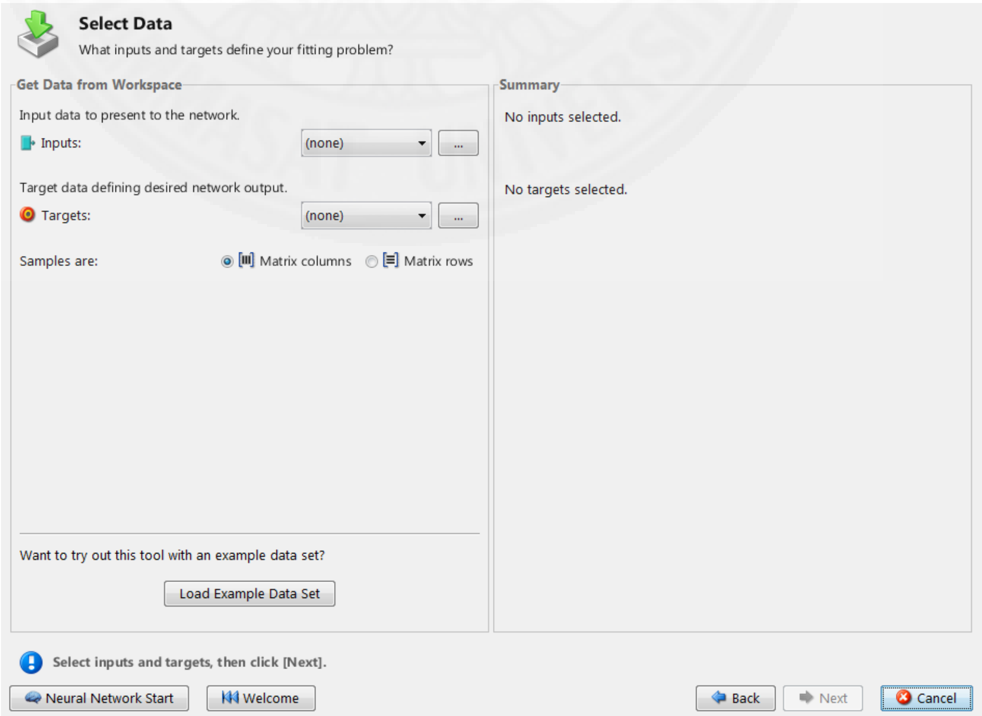
## Example method to construct ANN model by using MATLAB

1. From MATLAB command prompt, to open neural network fitting tool by typing "nftool".

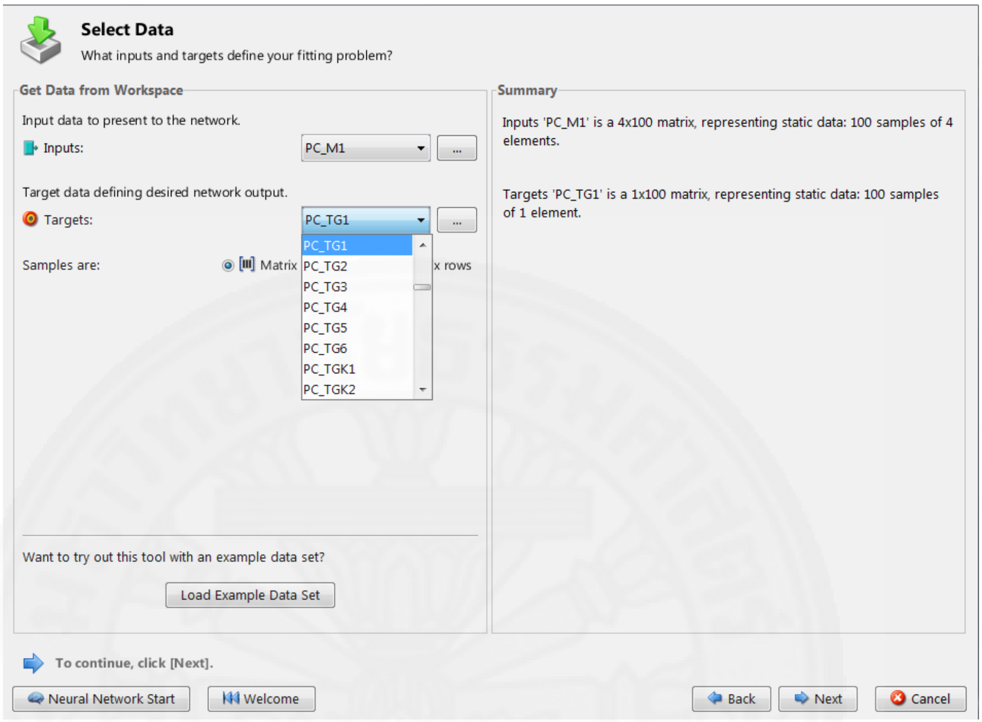



2. Select  button to go to input data and target Data screen.

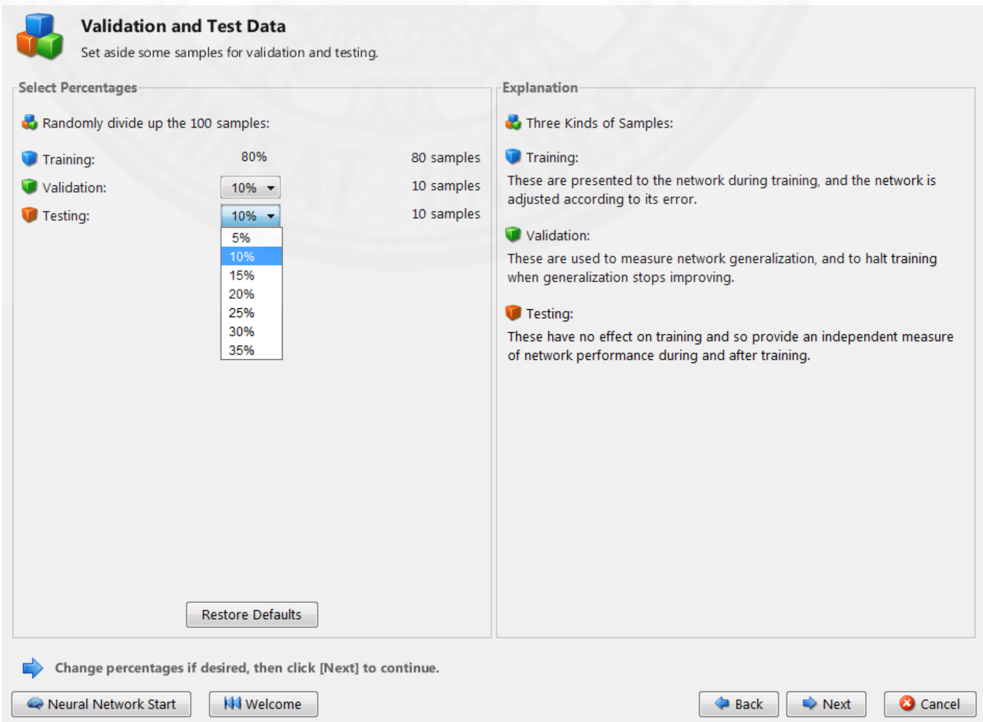




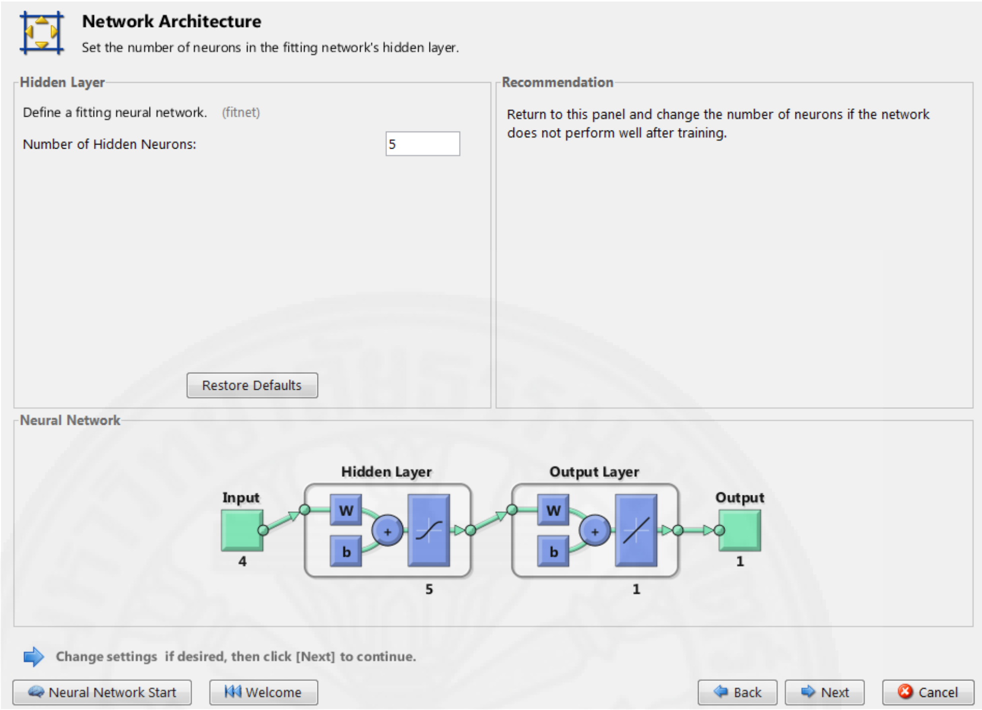
3. Select input data from drop down box of Input data and select target data from drop down box of Target data. Note that the input data and target data are input variables and target variables created in the workspace of MATLAB.



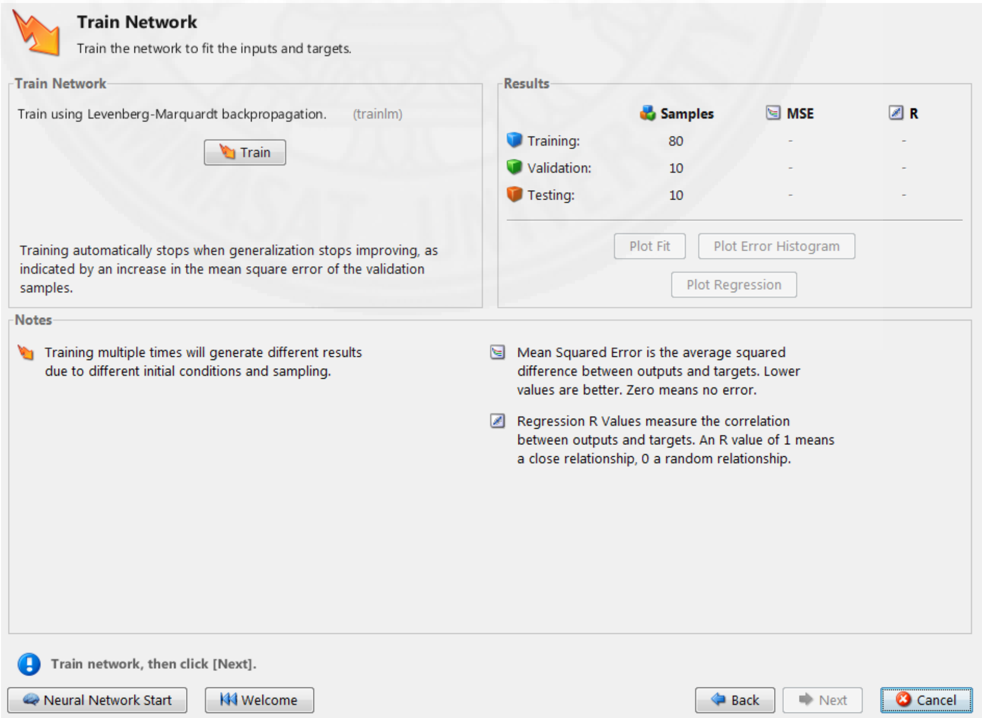

4. Select Next button to go to Validation and Test Data screen. From this screen select percentage for validation and testing.



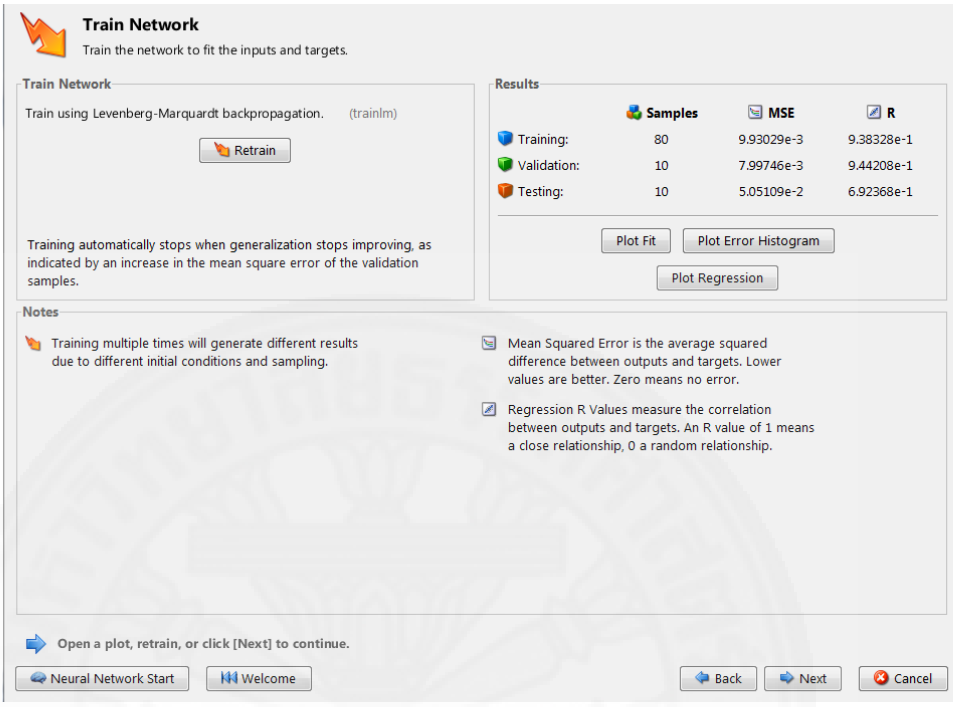
5. Select Next button to go to Network Architecture screen. In this screen, define the number of hidden neurons by typing the number.



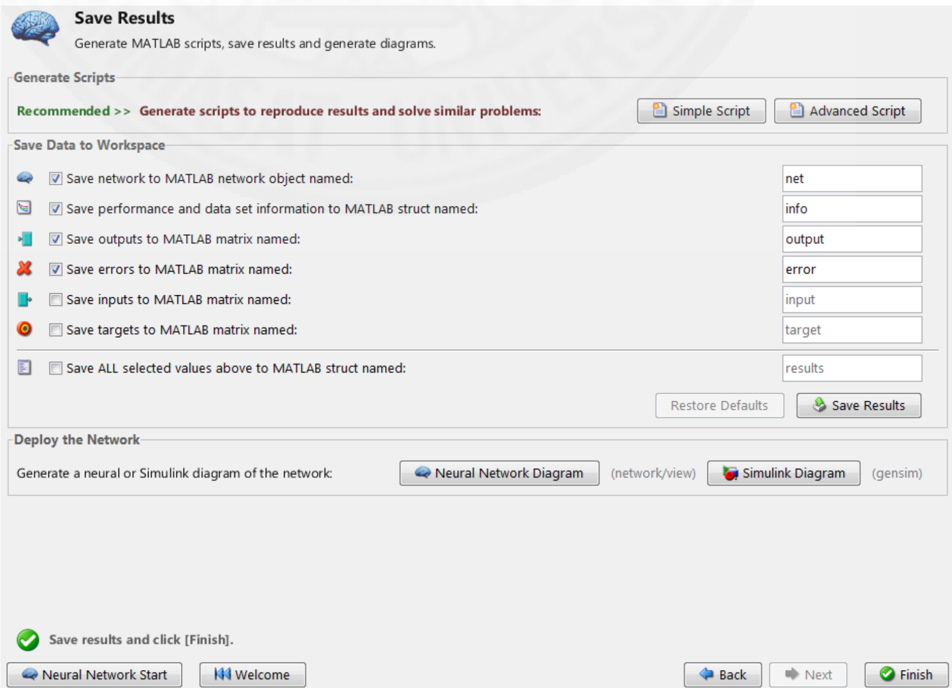

6. Select Next button to go to Train Network screen. Then press Train button to train the neural network model.



7. The model automatically runs and stops when approach the optimal point with displays the results of the training.




8. Select Next button to go to Evaluate Network screen. In this screen if user needs to add more data for evaluation, the input data and target data can be selected at this screen. If not, select Next button to go to Save Results screen.
9. From Save Results screen, the output from the model could be saved to workspace of MATLAB.



# APPENDIX E

## Inputs data for inventory control application

| Demand data | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Data | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | D11 | D12 | D13 | D14 | D15 |
| 1 | 2832 | 1006 | 921 | 2044 | 1785 | 1030 | 2259 | 1712 | 935 | 3166 | 1269 | 2309 | 2428 | 3351 | 2339 |
| 2 | 1966 | 2103 | 2082 | 1214 | 2700 | 2023 | 864 | 2819 | 1563 | 2230 | 2573 | 1993 | 1417 | 1529 | 2645 |
| 3 | 2553 | 3017 | 1033 | 1494 | 3156 | 3543 | 2900 | 870 | 1873 | 1847 | 1517 | 1642 | 2719 | 3094 | 2544 |
| 4 | 3589 | 2207 | 1293 | 3484 | 1548 | 3670 | 2985 | 3471 | 2011 | 2540 | 3230 | 1448 | 1612 | 1086 | 2535 |
| 5 | 2268 | 1497 | 2539 | 1404 | 1525 | 1583 | 1953 | 2079 | 3646 | 1454 | 1904 | 3079 | 1815 | 1700 | 1585 |
| 6 | 1552 | 3535 | 2634 | 3369 | 2370 | 3700 | 2698 | 3138 | 3700 | 1634 | 2974 | 2975 | 2954 | 2036 | 2899 |
| 7 | 2749 | 2708 | 3700 | 1608 | 2363 | 3542 | 3439 | 2046 | 2226 | 1167 | 1870 | 2724 | 2219 | 1767 | 2911 |
| 8 | 1858 | 899 | 2050 | 2973 | 1127 | 1796 | 3700 | 3700 | 2231 | 3463 | 2949 | 1478 | 2352 | 3382 | 3028 |
| 9 | 3550 | 3150 | 3375 | 2730 | 2500 | 3261 | 2112 | 1797 | 1909 | 1613 | 2706 | 1951 | 1448 | 2001 | 2867 |
| 10 | 3037 | 2013 | 3254 | 3221 | 2389 | 3525 | 2035 | 1682 | 1367 | 2193 | 3421 | 1543 | 2195 | 3645 | 3519 |
| 11 | 1262 | 3126 | 2246 | 1462 | 2800 | 1711 | 2076 | 1905 | 3178 | 3393 | 3372 | 2432 | 1948 | 2463 | 1778 |
| 12 | 3700 | 2638 | 2636 | 957 | 3462 | 3388 | 994 | 3655 | 2560 | 3674 | 1265 | 2325 | 1094 | 3700 | 3141 |
| 13 | 3461 | 3281 | 3225 | 3612 | 3536 | 2931 | 3245 | 2518 | 2167 | 1646 | 2645 | 1081 | 2323 | 930 | 879 |
| 14 | 1422 | 2474 | 1265 | 1321 | 2201 | 3550 | 2982 | 2945 | 2154 | 2917 | 2249 | 1598 | 999 | 2612 | 1445 |
| 15 | 1083 | 2545 | 3497 | 3202 | 3430 | 2426 | 3143 | 3106 | 2512 | 968 | 2116 | 2557 | 3604 | 1617 | 2261 |
| 16 | 2845 | 3067 | 1950 | 1931 | 3616 | 2132 | 2940 | 3301 | 2832 | 2033 | 2816 | 3644 | 3700 | 2595 | 1676 |
| 17 | 1436 | 2200 | 1970 | 803 | 2100 | 2942 | 3587 | 1821 | 2507 | 2231 | 1893 | 2119 | 2749 | 2685 | 1708 |
| 18 | 2435 | 3149 | 2600 | 1645 | 2759 | 3456 | 1351 | 1519 | 1745 | 2983 | 1817 | 2393 | 1295 | 3263 | 2464 |
| 19 | 1226 | 2713 | 2556 | 3048 | 3414 | 2511 | 1759 | 988 | 2117 | 2761 | 3424 | 1379 | 2199 | 1984 | 2868 |
| 20 | 3026 | 1480 | 2871 | 2991 | 1553 | 2804 | 2969 | 3040 | 1647 | 2667 | 2308 | 1734 | 2906 | 1865 | 1304 |
| 21 | 2520 | 2400 | 2982 | 3011 | 2800 | 2750 | 2378 | 2139 | 2882 | 1332 | 2338 | 1813 | 3412 | 2580 | 2465 |
| 22 | 3473 | 807 | 1553 | 1677 | 1257 | 1451 | 1827 | 3460 | 1731 | 2940 | 3253 | 1257 | 3312 | 3262 | 1549 |
| 23 | 2369 | 3532 | 2607 | 2627 | 3157 | 2925 | 1357 | 2191 | 2658 | 2613 | 3049 | 3524 | 3079 | 1331 | 3635 |
| 24 | 2682 | 2500 | 1573 | 3004 | 2000 | 1633 | 3207 | 1002 | 2210 | 2195 | 2183 | 3408 | 982 | 3015 | 3601 |
| 25 | 2528 | 3012 | 2500 | 2473 | 3381 | 2612 | 2259 | 2053 | 2426 | 1591 | 2192 | 2695 | 2238 | 2609 | 955 |
| 26 | 2017 | 3700 | 2670 | 2063 | 1950 | 1118 | 2122 | 2017 | 2421 | 3404 | 908 | 2732 | 3085 | 3226 | 2284 |
| 27 | 2628 | 1827 | 2756 | 2089 | 2550 | 1525 | 3540 | 3603 | 3019 | 2821 | 3355 | 997 | 1601 | 2326 | 2168 |
| 28 | 3415 | 2896 | 2510 | 2412 | 2438 | 2171 | 1103 | 2703 | 2314 | 984 | 2109 | 2066 | 1177 | 1494 | 2513 |
| 29 | 1870 | 3487 | 2706 | 2476 | 2700 | 1359 | 2923 | 2589 | 3597 | 3004 | 1854 | 2029 | 3408 | 3538 | 3239 |
| 30 | 3449 | 1933 | 1677 | 2659 | 2337 | 3547 | 2909 | 2051 | 3502 | 2110 | 1136 | 3491 | 2673 | 3504 | 986 |
| 31 | 3000 | 2400 | 3066 | 1550 | 3700 | 2571 | 1469 | 3542 | 1884 | 3483 | 3700 | 2547 | 1592 | 1786 | 1184 |
| 32 | 2558 | 1996 | 895 | 3435 | 2600 | 2173 | 2192 | 2364 | 2187 | 2739 | 2698 | 3640 | 2855 | 1639 | 1444 |
| 33 | 3473 | 3108 | 2189 | 2271 | 1487 | 3516 | 1793 | 2834 | 3229 | 1832 | 1894 | 2616 | 2253 | 1781 | 3499 |
| 34 | 3300 | 2300 | 3349 | 3700 | 3100 | 1127 | 1708 | 2450 | 1686 | 2669 | 1283 | 3096 | 3273 | 2975 | 3203 |
| 35 | 1950 | 3200 | 2996 | 3124 | 1768 | 1623 | 2049 | 3527 | 1968 | 1690 | 2726 | 2467 | 2620 | 1546 | 2285 |
| 36 | 1677 | 3654 | 2605 | 2221 | 1259 | 2412 | 3508 | 1789 | 2477 | 2421 | 3581 | 2246 | 2635 | 3031 | 2880 |
| 37 | 2958 | 3650 | 2355 | 3270 | 1000 | 2832 | 3605 | 912 | 3164 | 3612 | 1661 | 2585 | 2404 | 2321 | 2528 |
| 38 | 1400 | 3012 | 3287 | 2703 | 2200 | 2442 | 3501 | 2469 | 3076 | 3351 | 1770 | 2868 | 3127 | 3338 | 3210 |
| 39 | 2130 | 2080 | 2922 | 2344 | 3249 | 1691 | 2196 | 2199 | 2494 | 2454 | 2974 | 2160 | 2759 | 3079 | 3225 |
| 40 | 2708 | 1900 | 1700 | 3647 | 1255 | 1812 | 1812 | 2412 | 1465 | 1018 | 1866 | 1674 | 2203 | 3488 | 2884 |
| 41 | 2206 | 3445 | 1567 | 2136 | 1720 | 1649 | 1546 | 2086 | 3541 | 2833 | 3697 | 3700 | 3699 | 1829 | 2945 |
| 42 | 2566 | 2455 | 3624 | 1552 | 3368 | 2891 | 3301 | 2189 | 3562 | 2340 | 3094 | 3134 | 2464 | 3090 | 3700 |
| 43 | 3318 | 1550 | 1081 | 2725 | 2443 | 2625 | 2576 | 3430 | 1357 | 2547 | 3234 | 2621 | 3535 | 2018 | 2814 |
| 44 | 1172 | 2663 | 3665 | 3082 | 3000 | 2792 | 3066 | 3590 | 3634 | 3033 | 1467 | 3578 | 3677 | 2346 | 2894 |
| 45 | 2960 | 1550 | 1854 | 2245 | 3450 | 2821 | 2701 | 2365 | 3690 | 2578 | 3137 | 3486 | 2705 | 2891 | 1708 |
| 46 | 1133 | 2975 | 1290 | 3222 | 2184 | 2515 | 2040 | 2359 | 3129 | 3700 | 1963 | 2778 | 3647 | 2853 | 2237 |
| 47 | 3450 | 2700 | 3220 | 3400 | 2000 | 2424 | 3439 | 2383 | 3409 | 2622 | 3683 | 985 | 2000 | 2088 | 1506 |
| 48 | 1513 | 1400 | 2731 | 2098 | 3196 | 2072 | 2324 | 3560 | 3492 | 3319 | 2456 | 2866 | 1524 | 3544 | 2019 |
| 49 | 2422 | 2100 | 2826 | 3200 | 2900 | 3060 | 1015 | 1753 | 804 | 3425 | 3479 | 2706 | 2898 | 1439 | 1862 |
| 50 | 1250 | 1400 | 2400 | 1871 | 3400 | 1844 | 2525 | 2943 | 1426 | 2986 | 1718 | 3635 | 2200 | 2957 | 3493 |
| 51 | 3088 | 1888 | 3298 | 1600 | 2450 | 2844 | 2660 | 2965 | 1822 | 2370 | 1637 | 2079 | 2932 | 2179 | 2838 |
| 52 | 2500 | 1195 | 3346 | 3122 | 877 | 1159 | 2888 | 1481 | 2392 | 982 | 3124 | 3668 | 1594 | 1111 | 3374 |

Supply data

| Data | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | D11 | D12 | D13 | D14 | D15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4407 | 9059 | 12286 | 6936 | 9900 | 11178 | 3517 | 5190 | 9958 | 6725 | 4546 | 3433 | 9597 | 7617 | 5025 |
| 2 | 4468 | 6500 | 10391 | 1729 | 12864 | 2773 | 9356 | 5220 | 4797 | 11153 | 3000 | 7380 | 8672 | 10719 | 1207 |
| 3 | 10584 | 11984 | 6531 | 3000 | 8126 | 5271 | 13070 | 6757 | 7149 | 11239 | 1018 | 2156 | 9697 | 5340 | 10873 |
| 4 | 12338 | 700 | 5431 | 7234 | 8167 | 7471 | 11432 | 8621 | 7698 | 12141 | 2572 | 7436 | 4987 | 13070 | 2628 |
| 5 | 4284 | 5641 | 8085 | 5220 | 12264 | 2585 | 3145 | 10967 | 2164 | 13070 | 1937 | 2897 | 7758 | 1190 | 1433 |
| 6 | 10802 | 4477 | 10388 | 9000 | 8929 | 12980 | 6016 | 9471 | 7772 | 9689 | 3644 | 3249 | 1549 | 4244 | 10370 |
| 7 | 10985 | 5933 | 3378 | 6369 | 10000 | 6714 | 3263 | 5245 | 9608 | 1594 | 2377 | 3271 | 1169 | 6762 | 4784 |
| 8 | 7212 | 1710 | 8354 | 5379 | 8000 | 8618 | 10377 | 793 | 5897 | 1334 | 1885 | 2074 | 13070 | 801 | 3991 |
| 9 | 934 | 6700 | 9952 | 11749 | 9675 | 3100 | 11679 | 1761 | 11564 | 7755 | 8141 | 12867 | 3800 | 9596 | 9346 |
| 10 | 5220 | 12444 | 8449 | 7854 | 3839 | 1848 | 12087 | 10907 | 12114 | 2060 | 12248 | 12587 | 7937 | 7359 | 11445 |
| 11 | 11982 | 12487 | 8421 | 1040 | 4900 | 2337 | 8386 | 1105 | 2979 | 11103 | 12769 | 12014 | 12835 | 7000 | 4317 |
| 12 | 6369 | 9397 | 2500 | 2700 | 2170 | 1829 | 3922 | 2149 | 6281 | 1099 | 3007 | 11797 | 2478 | 10975 | 8538 |
| 13 | 5379 | 2408 | 13070 | 9887 | 6826 | 6501 | 1969 | 4251 | 5343 | 10762 | 6561 | 2365 | 2575 | 11355 | 12803 |
| 14 | 11749 | 11516 | 11022 | 887 | 10290 | 10397 | 11902 | 3956 | 10724 | 6846 | 5111 | 4848 | 4558 | 10433 | 998 |
| 15 | 7854 | 4180 | 2490 | 2874 | 2523 | 8907 | 2958 | 1153 | 10154 | 2265 | 7120 | 2540 | 12445 | 4203 | 7709 |
| 16 | 1040 | 1122 | 9326 | 2254 | 3702 | 1779 | 2721 | 7079 | 5950 | 12429 | 3600 | 2016 | 5212 | 5980 | 5436 |
| 17 | 7509 | 9982 | 1894 | 8709 | 7213 | 1287 | 11901 | 1250 | 9593 | 7820 | 929 | 4257 | 3645 | 9947 | 4060 |
| 18 | 9887 | 12688 | 4219 | 5439 | 8032 | 7459 | 10088 | 1921 | 13070 | 5835 | 5931 | 10212 | 2027 | 1453 | 3465 |
| 19 | 887 | 6956 | 2216 | 1900 | 12446 | 4008 | 11674 | 8275 | 10844 | 12474 | 2363 | 8412 | 5297 | 1451 | 9965 |
| 20 | 2874 | 3921 | 12555 | 11621 | 4604 | 12517 | 3770 | 10267 | 9757 | 9686 | 1355 | 7306 | 4999 | 3569 | 12070 |
| 21 | 2254 | 2940 | 7781 | 8600 | 3513 | 13070 | 10906 | 12773 | 1512 | 5985 | 12977 | 5906 | 1749 | 6937 | 2450 |
| 22 | 10540 | 2045 | 8730 | 9800 | 2491 | 2819 | 8788 | 7484 | 5392 | 12120 | 5853 | 1867 | 5803 | 12861 | 10259 |
| 23 | 7718 | 7000 | 10523 | 7008 | 10892 | 12670 | 1625 | 13070 | 8171 | 7054 | 13070 | 6749 | 1221 | 9394 | 3571 |
| 24 | 953 | 11578 | 4302 | 12156 | 8099 | 8140 | 5388 | 7257 | 6352 | 7335 | 10364 | 12245 | 8199 | 4124 | 11033 |
| 25 | 3953 | 5350 | 11341 | 969 | 2999 | 7961 | 1642 | 6758 | 696 | 9756 | 1600 | 10257 | 1146 | 3854 | 10536 |
| 26 | 5512 | 779 | 1502 | 1189 | 12690 | 11779 | 4481 | 4336 | 3162 | 3863 | 9244 | 7750 | 7647 | 11244 | 5571 |
| 27 | 1964 | 5000 | 2657 | 13070 | 1232 | 12574 | 3749 | 5638 | 9535 | 2169 | 9596 | 10058 | 10815 | 12055 | 9572 |
| 28 | 788 | 10053 | 1636 | 6549 | 3932 | 7317 | 11856 | 5948 | 1216 | 7667 | 8769 | 8684 | 3140 | 8453 | 6545 |
| 29 | 11205 | 1754 | 9700 | 6176 | 7665 | 11705 | 10935 | 931 | 12943 | 12480 | 7508 | 1658 | 5697 | 1172 | 10624 |
| 30 | 2935 | 10966 | 564 | 11170 | 2900 | 2685 | 5160 | 11639 | 1080 | 5387 | 2965 | 6786 | 7595 | 3377 | 2682 |
| 31 | 7133 | 1326 | 1564 | 2467 | 3253 | 1345 | 6587 | 847 | 9252 | 1491 | 10499 | 4672 | 819 | 11084 | 962 |
| 32 | 11851 | 599 | 600 | 825 | 1350 | 5950 | 11192 | 5719 | 6917 | 5878 | 3100 | 1240 | 6620 | 7732 | 3761 |
| 33 | 8843 | 1351 | 5150 | 7000 | 6600 | 8611 | 11038 | 10838 | 3014 | 3975 | 5041 | 1989 | 8568 | 12537 | 11953 |
| 34 | 2091 | 8300 | 10589 | 3400 | 1400 | 6945 | 3065 | 5173 | 7904 | 5316 | 12110 | 2666 | 2952 | 807 | 2545 |
| 35 | 3567 | 7538 | 1258 | 9000 | 1200 | 2961 | 7603 | 8043 | 1690 | 12036 | 11641 | 10044 | 11166 | 7731 | 2678 |
| 36 | 1272 | 12943 | 8855 | 5763 | 8844 | 10486 | 2317 | 12733 | 9281 | 5345 | 5470 | 5805 | 12954 | 3770 | 9839 |
| 37 | 6549 | 5999 | 6739 | 2034 | 4200 | 11053 | 2038 | 12619 | 10291 | 5167 | 4323 | 9992 | 12291 | 10945 | 1515 |
| 38 | 13070 | 7548 | 5028 | 8883 | 11266 | 12313 | 11443 | 12208 | 1774 | 4773 | 8273 | 3455 | 6750 | 2525 | 11428 |
| 39 | 6176 | 6000 | 12388 | 3100 | 4000 | 4964 | 11700 | 2501 | 1779 | 1857 | 12372 | 2131 | 2720 | 2852 | 10029 |
| 40 | 11170 | 6400 | 4200 | 3200 | 1677 | 1904 | 3536 | 2890 | 2109 | 2445 | 12357 | 7161 | 11960 | 2202 | 3339 |
| 41 | 10373 | 1699 | 10123 | 12000 | 899 | 6626 | 846 | 12772 | 1271 | 1150 | 8042 | 2759 | 3161 | 10930 | 2414 |
| 42 | 1623 | 12597 | 11000 | 904 | 1294 | 5438 | 4827 | 3780 | 3018 | 5687 | 4521 | 12730 | 12771 | 8950 | 3540 |
| 43 | 5322 | 6495 | 3500 | 9804 | 6067 | 1907 | 2801 | 6606 | 12508 | 2907 | 11596 | 12194 | 1205 | 2745 | 2801 |
| 44 | 4015 | 7100 | 5500 | 10080 | 12000 | 2755 | 5792 | 5035 | 4537 | 1941 | 11194 | 2783 | 8007 | 2206 | 12857 |
| 45 | 11340 | 13070 | 555 | 12526 | 1607 | 2712 | 1548 | 11743 | 3192 | 5626 | 12293 | 2334 | 1303 | 1769 | 11527 |
| 46 | 905 | 6387 | 8280 | 13070 | 8900 | 960 | 4777 | 3624 | 12816 | 1579 | 1451 | 10033 | 8274 | 9179 | 12639 |
| 47 | 9937 | 660 | 1005 | 8889 | 12601 | 2419 | 2998 | 2649 | 1481 | 7056 | 7237 | 12262 | 3755 | 7550 | 8717 |
| 48 | 10507 | 11000 | 1772 | 11166 | 6811 | 3476 | 3257 | 2951 | 12557 | 11355 | 9139 | 13070 | 11453 | 1945 | 2149 |
| 49 | 7624 | 5262 | 5477 | 1300 | 11357 | 5441 | 1530 | 2430 | 1494 | 2226 | 2437 | 766 | 12154 | 1952 | 8279 |
| 50 | 11910 | 1920 | 2670 | 6480 | 7111 | 12185 | 2970 | 12666 | 7149 | 12397 | 4574 | 6058 | 8333 | 3295 | 3797 |
| 51 | 5760 | 9000 | 9966 | 4870 | 911 | 6456 | 7230 | 8130 | 1980 | 981 | 3152 | 7836 | 9674 | 12908 | 1994 |
| 52 | 1683 | 6834 | 11334 | 12099 | 13070 | 10083 | 10434 | 9117 | 7735 | 5216 | 4376 | 10237 | 3067 | 5151 | 5204 |

Q from FIS model

| Data | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | D11 | D12 | D13 | D14 | D15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 7658 | 5670 | 6535 | 3092 | 6535 | 6535 | 6238 | 4302 | 6535 | 10607 | 5062 | 6258 | 9526 | 10410 | 4501 |
| 2 | 5346 | 2483 | 6535 | 6535 | 10731 | 6535 | 6008 | 8805 | 4771 | 6535 | 5676 | 3665 | 5231 | 6535 | 6535 |
| 3 | 10462 | 10645 | 2431 | 6535 | 10346 | 8868 | 10645 | 2777 | 3350 | 6535 | 6535 | 6535 | 10624 | 8954 | 10351 |
| 4 | 10731 | 6535 | 4002 | 10577 | 4849 | 10445 | 10645 | 10387 | 4076 | 10326 | 6535 | 3739 | 4547 | 6535 | 4785 |
| 5 | 5543 | 3730 | 8583 | 4454 | 6535 | 6535 | 6535 | 6535 | 6535 | 6535 | 6535 | 6535 | 4151 | 6535 | 6535 |
| 6 | 6535 | 7929 | 10645 | 10552 | 7187 | 10645 | 9853 | 10578 | 10374 | 6398 | 6980 | 6535 | 6535 | 5406 | 10645 |
| 7 | 10731 | 9736 | 6668 | 2667 | 7936 | 10609 | 6535 | 4234 | 6302 | 6535 | 6535 | 6539 | 6535 | 2784 | 8283 |
| 8 | 3547 | 6535 | 4865 | 8826 | 4645 | 5169 | 10645 | 6535 | 3384 | 6535 | 6535 | 6535 | 7848 | 6535 | 7377 |
| 9 | 6535 | 10612 | 10645 | 10731 | 10230 | 6535 | 6535 | 6535 | 6535 | 4147 | 10283 | 6535 | 5911 | 6287 | 10551 |
| 10 | 8616 | 6535 | 10345 | 10420 | 4471 | 6535 | 6535 | 6535 | 6535 | 6535 | 10645 | 6535 | 4371 | 10470 | 10645 |
| 11 | 6535 | 10645 | 4943 | 6535 | 8217 | 6535 | 4902 | 6535 | 6535 | 10645 | 10645 | 9964 | 6535 | 7083 | 5323 |
| 12 | 10403 | 10562 | 6535 | 6535 | 6535 | 6535 | 5771 | 6535 | 8854 | 6535 | 6535 | 7202 | 6535 | 10645 | 10367 |
| 13 | 8826 | 6535 | 10645 | 10731 | 10671 | 10589 | 6535 | 5613 | 4113 | 6535 | 10640 | 6535 | 5917 | 6535 | 6535 |
| 14 | 6535 | 10550 | 6535 | 6535 | 6535 | 10645 | 10645 | 7337 | 6535 | 10582 | 4398 | 4712 | 5048 | 10645 | 6535 |
| 15 | 4459 | 6126 | 6535 | 6535 | 6535 | 8561 | 6535 | 6535 | 10367 | 6535 | 3309 | 5294 | 10645 | 5453 | 4089 |
| 16 | 6535 | 6535 | 5974 | 6535 | 6942 | 6535 | 6535 | 10533 | 9760 | 6535 | 6929 | 6535 | 8795 | 9417 | 3995 |
| 17 | 3991 | 6535 | 6535 | 5461 | 3549 | 6535 | 10645 | 6535 | 10031 | 4228 | 6535 | 5392 | 6981 | 10645 | 5615 |
| 18 | 10015 | 10645 | 7453 | 4162 | 10372 | 10447 | 6535 | 6535 | 6535 | 9601 | 3336 | 8867 | 6535 | 6535 | 3143 |
| 19 | 6535 | 10559 | 5294 | 6535 | 10731 | 5160 | 6535 | 4773 | 6535 | 10645 | 6535 | 4933 | 4170 | 6535 | 10645 |
| 20 | 6535 | 5772 | 10645 | 10731 | 5195 | 10645 | 7125 | 10645 | 6480 | 10622 | 6283 | 3566 | 8537 | 6177 | 6535 |
| 21 | 4579 | 3992 | 10371 | 10451 | 6762 | 10645 | 8484 | 6535 | 6535 | 3260 | 7513 | 3372 | 6535 | 9783 | 2857 |
| 22 | 10731 | 6535 | 5297 | 6533 | 6535 | 6535 | 5362 | 10442 | 4051 | 10645 | 9626 | 6535 | 9557 | 10645 | 6535 |
| 23 | 5967 | 10550 | 10645 | 10630 | 10731 | 10645 | 6535 | 6535 | 10277 | 10538 | 10645 | 10602 | 6535 | 6052 | 6895 |
| 24 | 6535 | 10427 | 5340 | 10731 | 4767 | 4614 | 9014 | 3499 | 2717 | 3604 | 6535 | 10645 | 4684 | 7528 | 10645 |
| 25 | 5528 | 8966 | 10427 | 3159 | 6535 | 10328 | 6535 | 2778 | 3258 | 6478 | 6535 | 10645 | 6535 | 7221 | 6535 |
| 26 | 4060 | 6535 | 6535 | 6535 | 6535 | 6535 | 5136 | 5302 | 3405 | 7231 | 5880 | 10379 | 10403 | 10645 | 3822 |
| 27 | 6535 | 4531 | 6535 | 6535 | 5345 | 6535 | 7101 | 9336 | 10591 | 6535 | 10604 | 6535 | 6535 | 7250 | 6259 |
| 28 | 6535 | 10645 | 4151 | 5736 | 3528 | 3580 | 6535 | 9758 | 6110 | 4036 | 5341 | 5244 | 6535 | 4980 | 8017 |
| 29 | 6535 | 6535 | 10625 | 6671 | 10470 | 6535 | 10645 | 6086 | 10645 | 10645 | 3833 | 6535 | 9414 | 6535 | 10645 |
| 30 | 6535 | 6535 | 6535 | 10731 | 5723 | 6535 | 8732 | 6535 | 6535 | 4057 | 6535 | 10595 | 10416 | 6666 | 6535 |
| 31 | 10601 | 3992 | 6535 | 6535 | 6535 | 5653 | 2510 | 6535 | 5889 | 6535 | 10645 | 6651 | 6535 | 6535 | 6535 |
| 32 | 10489 | 6535 | 6535 | 6535 | 6399 | 3310 | 6535 | 4384 | 3018 | 9660 | 6535 | 6535 | 10628 | 4119 | 5955 |
| 33 | 10513 | 6535 | 4350 | 3202 | 2471 | 10384 | 6535 | 10645 | 6535 | 5711 | 4482 | 6535 | 5112 | 6535 | 10645 |
| 34 | 6535 | 4884 | 10645 | 6657 | 6535 | 3059 | 6535 | 4965 | 4331 | 8924 | 6535 | 6535 | 6535 | 6535 | 6535 |
| 35 | 6257 | 10429 | 6535 | 10552 | 6535 | 6535 | 3955 | 10308 | 6535 | 6535 | 10645 | 10585 | 10645 | 4117 | 6535 |
| 36 | 6535 | 10645 | 10368 | 3694 | 5604 | 9407 | 6535 | 6535 | 9847 | 5163 | 9118 | 3510 | 10645 | 7125 | 10645 |
| 37 | 10728 | 9829 | 4431 | 6535 | 5631 | 10645 | 6535 | 6535 | 10645 | 8740 | 5317 | 10545 | 9160 | 7129 | 4611 |
| 38 | 6535 | 10427 | 8572 | 10523 | 6535 | 10310 | 10645 | 10572 | 6535 | 8270 | 4771 | 6759 | 10602 | 6535 | 10645 |
| 39 | 3020 | 3239 | 10645 | 5570 | 7235 | 4574 | 6535 | 6535 | 3718 | 2460 | 10645 | 6535 | 6535 | 6535 | 10645 |
| 40 | 10731 | 2642 | 5456 | 6535 | 6535 | 6535 | 6216 | 3663 | 6535 | 6535 | 6535 | 3367 | 6535 | 6535 | 6621 |
| 41 | 6535 | 6535 | 6535 | 6535 | 6535 | 2572 | 6535 | 6535 | 6535 | 6535 | 10308 | 6535 | 6535 | 6535 | 6535 |
| 42 | 5680 | 10633 | 10645 | 6535 | 6535 | 9077 | 8334 | 5934 | 6535 | 3718 | 7979 | 10645 | 10599 | 10464 | 6859 |
| 43 | 8750 | 2491 | 6257 | 10731 | 6096 | 6535 | 5748 | 10631 | 6535 | 5053 | 10645 | 10645 | 6535 | 6535 | 6535 |
| 44 | 5820 | 10528 | 9157 | 10731 | 10731 | 6535 | 9542 | 8581 | 7998 | 6535 | 6535 | 6535 | 10316 | 5342 | 10645 |
| 45 | 10731 | 6535 | 6535 | 6535 | 6535 | 6535 | 6535 | 8187 | 6535 | 8431 | 10645 | 6535 | 6535 | 6535 | 6535 |
| 46 | 6535 | 10408 | 4779 | 10731 | 5662 | 4281 | 4795 | 5029 | 10645 | 6535 | 6535 | 10645 | 10302 | 10515 | 6535 |
| 47 | 10731 | 6535 | 6535 | 10525 | 6535 | 3317 | 6535 | 4435 | 6535 | 10537 | 10498 | 6535 | 5962 | 3887 | 5282 |
| 48 | 6535 | 6535 | 6535 | 6535 | 10674 | 6286 | 5892 | 6535 | 10645 | 10645 | 9651 | 10645 | 6535 | 6535 | 6535 |
| 49 | 6956 | 4213 | 9127 | 6535 | 10731 | 9081 | 6535 | 6535 | 6535 | 6535 | 6535 | 6535 | 10645 | 6535 | 4778 |
| 50 | 6535 | 6535 | 3992 | 2451 | 10606 | 6535 | 4511 | 10645 | 3350 | 10645 | 5030 | 9914 | 4841 | 6568 | 7156 |
| 51 | 9371 | 5603 | 10645 | 4889 | 2425 | 10517 | 10499 | 10286 | 6535 | 4785 | 6535 | 4247 | 10620 | 6535 | 6535 |
| 52 | 4015 | 2895 | 10645 | 10731 | 6535 | 6535 | 10645 | 5735 | 6470 | 4270 | 7814 | 10645 | 6535 | 4349 | 8785 |

# APPENDIX F

## Example calculation of order quantity and inventory cost

| Week | Demand | Supply | Fuzzy Q | $R_0 = 0$, $R_i = 300$<br>Beginning inventory | | | $Ie_0 = 0$<br>Ending inventory | Ordering | | Holding | | Shortage | | Total Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | $I_{i-1} < R$ ?<br>If yes, order<br>$Q_i \geq S_i$ ? | | If no, not order | $Ie_i = Ib_i - D_i$ | $Ib_i = Ie_{i-1}$ ?<br>If yes, $Q_o = 0$<br>If no, $Q_o = 1$<br>$C_o = 100$ | | $Q_h = 0.5(Ib_i+Ie_i)$<br>$C_h = 0.05$ | | $Ib_i < D_i$ ?<br>If yes, $Q_s = D_i - Ib_i$<br>If no, $Q_s = 0$<br>$C_s = 59$ | | |
| | | | | If yes, $Q_i=S_i$ | If no, $Q_i=Q_i$ | $Q_i = 0$ | | | | | | | | |
| i | $D_i$ | $S_i$ | $Q_i$ | $Ib_i = Q_i + Ie_{i-1}$ | | | | $Q_o$ | Cost | $Q_h$ | Cost | $Q_s$ | Cost | |
| 1 | $D_1$=280 | $S_1$=440 | $Q_1$=760 | 440 | | | 160 | 1 | 100 | 300 | 15.00 | 0 | 0 | 115.00 |
| 2 | 200 | 450 | 530 | 610 | | | 410 | 1 | 100 | 510 | 25.50 | 0 | 0 | 125.50 |
| 3 | 250 | 1060 | 1040 | | | 410 | 160 | 0 | 0 | 285 | 14.25 | 0 | 0 | 14.25 |
| 4 | 360 | 1230 | 1070 | | 1230 | | 870 | 0 | 0 | 1050 | 52.50 | 0 | 0 | 52.50 |
| 5 | 225 | 423 | 555 | | | 870 | 645 | 0 | 0 | 757.5 | 37.88 | 0 | 0 | 37.88 |
| 6 | 155 | 1080 | 653 | | | 645 | 490 | 0 | 0 | 567.5 | 28.38 | 0 | 0 | 28.38 |
| 7 | 275 | 1099 | 1073 | | | 490 | 215 | 0 | 0 | 352.5 | 17.63 | 0 | 0 | 17.63 |
| 8 | 186 | 720 | 355 | | 570 | | 384 | 1 | 100 | 477 | 23.85 | 0 | 0 | 123.85 |
| 9 | 355 | 100 | 650 | | | 384 | 29 | 0 | 0 | 206.5 | 10.33 | 0 | 0 | 10.33 |
| 10 | 560 | 520 | 860 | 549 | | | -11 | 1 | 100 | 269 | 13.45 | 11 | 649 | 762.45 |

# BIOGRAPHY

| | |
|---|---|
| Name | Mr. Prasert Aengchuan |
| Date of Birth | August 9, 1971 |
| Educational Attainment | 1998: Master of Engineering (Industrial System Engineering)<br>Asian Institute of Technology<br>1994: Bachelor of Engineering (Mechanical Engineering)<br>Mahidol University |
| Work Position | Lecturer, Faculty of Industrial Technology, Valaya Alongkorn Rajabhat University under the Royal Patronage |
| Scholarship | 2012: Full scholarship to study Ph.D. from Valaya Alongkorn Rajabhat University under the Royal Patronage<br>1997: Full scholarship to study M. Eng. from the Royal Government of the Netherlands |
| Work Experiences | 2008 – present: Lecturer<br>Valaya Alongkorn Rajabhat University under the Royal Patronage<br>2004 – 2008: Quality Assurance Manager<br>The Siam Gypsum Industry (Saraburi) Co., Ltd.<br>2002 – 2004: Quality Assurance Manager<br>The Siam Gypsum Industry (Songkhla) Co., Ltd.<br>1999 – 2001: Production Engineer<br>The Siam Gypsum Industry (Songkhla) Co., Ltd.<br>1994 – 1997: Project Engineer & Production Engineer<br>Siam Fiberglass Co., Ltd. |