

**DEVELOPMENT OF INTEGRATED INVENTORY MODEL BASED ON  
OPTIMIZED FUZZY SUGENO MODEL**

**THESIS**

**Submitted to International Program**

**Faculty of Industrial Technology in Partial Fulfillment of**

**The Requirement for the degree of Sarjana Teknik Industri at**

**Universitas Islam Indonesia**



**By**

**R. Achmad Chairdino Leuveano**

**07 522 100**

**INTERNATIONAL PROGRAM**

**DEPARTMENT OF INDUSTRIAL ENGINEERING**

**FACULTY OF INDUSTRIAL TECHNOLOGY**

**UNIVERSITAS ISLAM INDONESIA**

**YOGYAKARTA**

**2011**

THESIS APPROVAL OF SUPERVISOR

DEVELOPMENT OF INTEGRATED INVENTORY MODEL BASED  
ON OPTIMIZED FUZZY SUGENO MODEL

THESIS

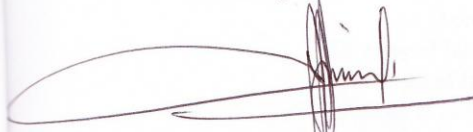
By

Name : R. Achmad Chairdino Leuveano

Student Number : 07 522 100

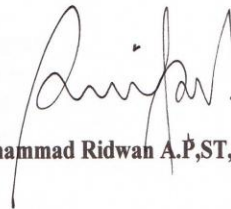
Yogyakarta, 15 March 2011

Main Supervisor



Prof. Dr. Ir. R. Chairul Saleh, M.Sc.

Co-Supervisor



Dr. Muhammad Ridwan A.P., ST, M.Sc.

THESIS APPROVAL OF EXAMINATION COMMITTEE

DEVELOPMENT OF INTEGRATED INVENTORY MODEL BASED ON  
OPTIMIZED FUZZY SUGENO MODEL

THESIS

By

Name : R. Achmad Chairdino Leuveano

Student Number : 07 522 100

Was defended in front of Examination Committee in Partial Fulfillment of  
the Requirements for the degree of Sarjana Teknik Industri  
Fakultas Teknologi Industri Universitas Islam Indonesia  
Yogyakarta, 24 March 2011

Examination Committee

Muhammad Ridwan A.P, ST, M.Sc.  
Examination Committee Chair

Dr. Eng.Ir.Rudi Suhradi Rachmat, M.Eng  
Member I

Dr.Ir.Bagus Made Arthaya, M.Eng  
Member II

Accepted by,  
Director of International Program  
Department of Industrial Engineering  
Faculty of Industrial Technology  
Universitas Islam Indonesia



Drs.M.Ibnu Mastur, MSIE

28  
3 2011

**THIS THESIS IS DEDICATED TO:**

Okaasan, Mrs Diah Purnamawati

Otoosan, Prof. Dr. Ir. Chairul Saleh, M.Sc

Niisan, Nur Rachman Dzaki Ullah

Imouto, Dinovita Nurul Haq



## MOTTO

“ALLAH will lift up faithful peoples and knowledgeable peoples between us several steps higher” (QS. Almujaadillah 11)

“In facing the change and become the greatest peoples, there is one way must doing, that is fixing our self in continuously”

"Everybody that go out to finding the knowledge, then they is in ALLAH's way until home" (HR. Turmudzi)



## PREFACE



**Assalamualikum Wr.Wb**

Alhamdulillah robbil a'lamin. First of all, I would like to say thanks to Allah SWT that always give us bless and mercy for all mankind who had faith and worship to God. Because of His bless and mercy, I can finish my thesis with Title **DEVELOPMENT OF INTEGRATED INVENTORY MODEL BASED ON OPTIMIZED FUZZY SUGENO MODEL**. This Thesis is part of requirement to get bachelor's degree of Industrial Engineering Department at University Islam Indonesia. In this opportunity I would like to say special thanks and deepest respect to my main supervisor Prof. Dr. Chairul Saleh, M.Sc. and co-supervisor Dr. Muhammad Ridwan Andi Purnomo, ST, M.Sc. that always give support, advice, guidance, and suggestion to me so that I can finish my thesis.

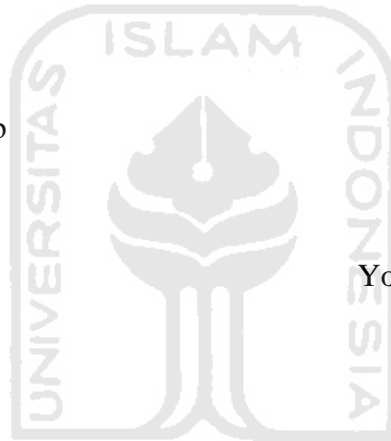
There are many people who have involved in support me to finish my thesis and make this thesis are come true and I would like to express appreciation to:

1. My lovely Father and Mother, Prof. Dr. Ir. Chairul Saleh, M.Sc. and Diah Purnamawati.
2. My lovely brother and sister, Nur Rachman Dzaki Ullah and Dinovita Nurul Haq.
3. My family for their support.
4. Dr. Muhammad Ridwan Andi Purnomo, ST, M.Sc. as my supervisor and lecturer.
5. Mr. Muhammad Ridwan's Family.
6. Dr. Eng. Ir. Rudi Suhradi Rachmat, M.Eng as my supervisor and my lecturer

7. Mr Rudi's Family.
8. Dr. Ir. Bagus Made Arthaya, M.Eng as my lecturer
9. Mr. Bagus Made Arthaya's family
10. All my friends of International Program FTI UII 2007, thanks for everything.
11. All my friends of International Program FTI UII 2008, 2009, and 2010.
12. Mrs. Diana, and All of IP FIT Lecturers.
13. All my friends of Senior High School Muhammadiyah I
14. PT FUMIRA JAKARTA

May God Almighty, Allah SWT bless Us. Amiin

Wassalamualaikum Wr. Wb



Yogyakarta, March 26, 2011

R. Achmad Chairdino Leuveano

## TABLE OF CONTENT

<b>COVER</b>	<b>i</b>
<b>APPROVAL OF SUPERVISOR PAGE</b>	<b>ii</b>
<b>APPROVAL OF EXAMINATION</b>	<b>iii</b>
<b>DEDICATION</b>	<b>iv</b>
<b>MOTTO</b>	<b>v</b>
<b>PREFACE</b>	<b>vi</b>
<b>TABLE OF CONTENT</b>	<b>viii</b>
<b>LIST OF TABLE</b>	<b>xii</b>
<b>LIST OF FIGURE</b>	<b>xiv</b>
<b>ABSTRACT</b>	<b>xvi</b>
<b>CHAPTER I INTRODUCTION</b>	<b>1</b>
1.1 Background	1
1.2 Problem Formulation	3
1.3 Problem Limitation	3
1.4 Research Objective	3
1.5 Research Benefit	4
1.6 Thesis Structure	4
<b>CHAPTER II LITERATURE REVIEW</b>	<b>6</b>
2.1 Previous Research	6
2.2 Basic Theory	8
2.2.1 Just in Time (JIT)	8





2.2.2 Just in Time Purchasing	9
2.2.3 Lead Time	11
2.2.4 Order/Setup Cost	12
2.2.5 Holding Cost	12
2.2.6 Crash Cost	13
2.2.7 Mathematical Model	14
2.2.8 Forecasting	15
2.2.9 Fuzzy Logic	16
2.2.10 Genetic Algorithm	22
2.2.11 Genetic Algorithm Procedures	23
2.2.12 The Comparison Between Regular Optimization with GA	25
2.2.13 Genetic Algorithm Component	26
<b>CHAPTER III RESEARCH METHODOLOGY</b>	<b>33</b>
3.1 Research Object	33
3.2 Mathematical Model	33
3.2.1 Mathematical Notation	33
3.2.2 Fuzzy Logic Model	36
3.2.3 A Basic Model Integrated Inventory	39
3.2.4 Investment in Quality Improvement	40
3.2.5 Fractional per Unit Time Opportunity Cost of Capital	44
3.2.6 Objective Function	44
3.2.7 Genetic Algorithm	44
3.3 Model Validation	47
3.4 Data Requirement	50

3.5 Data Analysis	50
3.6 Analysis Tool	51
3.7 Research Flow Diagram	51
<b>CHAPTER IV DATA COLLECTING AND PROCESSING</b>	<b>53</b>
4.1 Data Collecting	53
4.2 Data Processing	56
4.2.1 Mathematical and Fuzzy Modeling	57
4.2.2 Integrated Inventory Model for Probabilistic	61
4.2.2.1 Data Integrated Inventory Model	61
4.2.2.2 Total Relevant Cost for Probabilistic Demand	71
4.2.3 Objective Function/Fitness Function	80
4.3 GA optimization	81
4.3.1 Initialization	81
4.3.2 Selection	82
4.3.3 Crossover	83
4.3.4 Mutation	83
4.3.5 Problem Definition in GA Generator	84
4.3.6 Termination	86
4.3.7 Genetic Algorithm Optimization Result	87
4.4 Fuzzy Model after Optimization	87
4.5 Total Relevant Cost after Optimization	89
4.6 Summary result	90
<b>CHAPTER V. DISCUSSION</b>	<b>91</b>

<b>CHAPTER VI. CONCLUSION AND RECOMMENDATION</b>	<b>94</b>
6.1 Conclusion	94
6.2 Recommendation	95
<b>REFERENCES</b>	<b>96</b>
<b>APPENDICES</b>	<b>101</b>



## LIST OF TABLE

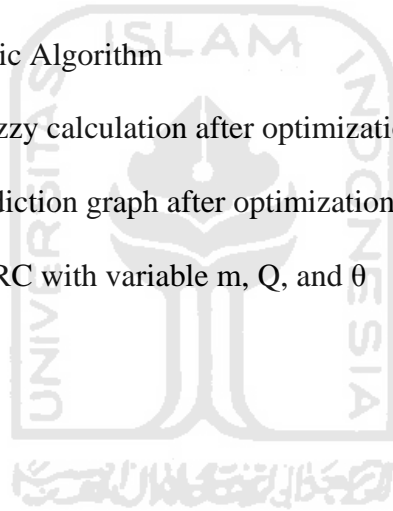
Table 2.1 Characteristic Conventional system Vs JIT system	9
Table 2.2 The Effect of JIT Purchasing Practice	10
Table 4.1 Actual Demand	53
Table 4.2 Lead Time Data	54
Table 4.3 Element Cost Data	54
Table 4.4 Actual Inventory and Production	55
Table 4.5 Setup Cost	55
Table 4.6 Production Cost	55
Table 4.7 Primary Holding Cost	55
Table 4.8 Percentage Decrease in $\theta$ and Rupiah Increase in $q(\theta)$	56
Table 4.9 Back Order and Gross Marginal Data	56
Table 4.10 Defective Unit Data	56
Table 4.11 Production Rate	56
Table 4.12 Rule Weight	59
Table 4.13 Number of Demand	62
Table 4.14 Expected Demand during Lead Time	63
Table 4.15 Production Rate of Initial Forecasting Result	65
Table 4.16 Unit Production Cost	66
Table 4.17 Parameter Input for TRC	71
Table 4.18 Summaries of the solution procedure for $m, Q, \theta_i$ , and $L$	80
Table 4.19 Summaries of Initial Integrated Inventory Model	80
Table 4.20 Comparison result of genetic algorithm optimization	87
Table 4.21 Parameter Input after optimization	89



## LIST OF FIGURE

Figure 2.1 Linier Representation up	18
Figure 2.2 Linier Representation down	18
Figure 2.3 Triangle Curve Representations	19
Figure 2.4 Trapezoid Curve Representation	19
Figure 2.5 Shoulder Shaped Representation for Variable Temperature	20
Figure 2.6 GA structure	24
Figure 2.7 Comparison between Conventional Method and Genetic Algorithm	25
Figure 2.8 One Point Crossover	29
Figure 2.9 Crossover with Two Points	29
Figure 2.10 Crossover with more than two points	30
Figure 2.11 Arithmetic crossover illustration	30
Figure 2.12 PMX steps 1	30
Figure 2.13 PMX steps 2	31
Figure 2.14 PMX steps 3	31
Figure 2.15 PMX steps 4	31
Figure 2.16 Mutation Process	32
Figure 2.17 Display of Generator v1.10	32
Figure 3.1 Representation of (D)	37
Figure 3.2 Representation of (I)	37
Figure 3.3 Representation of Chromosome	46
Figure 3.4 Research Framework	52
Figure 4.1 Fuzzy Set of (D)	57
Figure 4.2 Fuzzy Set of (I)	58

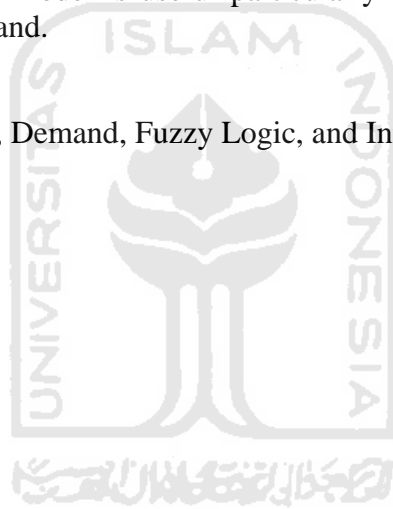
Figure 4.3 Summary of Fuzzy Calculation	60
Figure 4.4 The comparison between actual and prediction of TP value	61
Figure 4.5 The value of TRC with variable m, Q, and $\theta$	79
Figure 4.6 The representation of chromosomes	82
Figure 4.7 Representation of selection	82
Figure 4.8 Representation of two cut points crossover	83
Figure 4.9 Representation of mutation	84
Figure 4.10 Problem Definitions in Generator	84
Figure 4.11 Searching process of GA	86
Figure 4.12 Status of Genetic Algorithm	86
Figure 4.13 Summary of fuzzy calculation after optimization	88
Figure 4.14 Actual and prediction graph after optimization	89
Figure 4.15 The value of TRC with variable m, Q, and $\theta$	90



## ABSTRACT

Just in Time (JIT) purchasing has important role to solve the problem in manufacturing system. The problems that often occurred in JIT environment which includes maintaining a high quality product, small lot sizes, frequent of delivery, short lead time, and close supplier ties. The importance of establishing JIT purchasing with supplier is to solve the problem together. This issue is paralleled in resources dependence theory, which predicts how organization responds to uncertainty within their external environment. Based on the dependence with supplier, hence integrated inventory model is established. The purpose of integrated inventory model is to minimize total relevant cost which includes cost of ordering/ setup, holding cost, quality improvement investment and crashing cost by simultaneously optimizing the order quantity, lead time, process quality and number of deliveries. The current research proposes development of integrated inventory model based on optimized fuzzy logic model to forecast the number of production in response to uncertainty in demand. This development model is useful particularly for JIT inventory system to respond uncertainty in demand.

Keywords: JIT, Purchasing, Demand, Fuzzy Logic, and Integrated Inventory model





# CHAPTER I

## INTRODUCTION

### 1.1 Background

In recent years, supply chain management has become practice in manufacturing system. Just in Time (JIT) production system plays important role in regulating the supply chain (Pan and Yang, 2004). Some companies use JIT production system to gain and maintain competitive advantage with compressing lead time to perform activities associated with delivering high quality products to customers. Moreover, many companies have managed to be succeed due to devoting their attention on reduce inventory costs, lead times and improve quality simultaneously in a dynamic competitive environment. The characteristic of JIT system consistent on high quality, correct lot sizes, continuous delivery, short lead-time, and close to the suppliers (Pan and Yang, 2004).

Martinich (1997) mentioned that companies have found that there are significant benefits of single building relationships towards their suppliers. Moreover, in a JIT environment, a close cooperation exists between suppliers and buyers to solve problems together. In this point, integrated inventory give benefit to maintained long-term relationship between them. Pan and Yang (2004) conduct the research involved two organizations in JIT purchasing, namely the supplier and buyer. This model development has a goal to minimize the Total Relevant Cost (TRC), which includes cost of purchasing, vendor setup, storage, improving quality and accelerating cost of lead-time (crash cost of lead-time). It is important that TRC should be minimized by

simultaneously optimizing the order quantity, lead time, process quality and number deliveries with the conditions of demand and supply lead-time are deterministic. The minimum TRC represents optimal integrated inventory cost of buyer and vendor.

In the dynamic business environment, demand is always fluctuating (Ho, 1989). Deterministic demand is not appropriate if being implemented in dynamic business environment. Monika (2010) has been research with changing the deterministic demand and lead time to be probabilistic and uncertainty demand in integrated model proposed by Pan and Yang (2004). This research showed that the value of the total relevant cost between supplier and buyer is always changed because the number of demand is always changed.

The problems faced in this research are the existence of a probabilistic demands which difficult to control. So that both buyer and supplier have difficulty in optimizing the production quantity, process quality, lead time, and number deliveries.

Further research uses with the same model developed by Pan and Yang (2004). Since, it is more appropriate to develop integrated inventory model for probabilistic demand. This research presents a model to determine the number of production when demand is uncertainty so that forecasting method is needed to forecast the number of production. It will be the function of demand and inventory. The forecasting will be carried out based on fuzzy logic model.

The forecasting result will give effect to the total relevant cost in the integrated inventory model. If the forecasting result has a big error or more than ten percent, the model will be poor in accuracy. Therefore minimize the error of prediction and total

relevant costs are parameters in optimizing integrated inventory model. Both parameters will be optimized using Genetic Algorithm (GA).

## **1.2 Problem Formulation**

Based on the mentioned background, the main problem of this research can be formulated is as follows:

- a. What is the model based on optimized fuzzy logic model to conduct forecasting in dynamic demand environment?
- b. How to optimize the relevant cost using GA?

## **1.3 Problem Limitation**

The limitations can be described as the following:

- a. The research object is focused on PT. Narigus as supplier and PT. Aseli Dagadu as a purchaser.
- b. This research involves a long-term sole-supplier relationship with a supplier.
- c. The aim of this research is focused on developing a model to meet uncertainty in demand and not comparing the proposed model with another.
- d. All of the cost data are predetermined and will not change along examined period.

## **1.4 Research Objective**

The purposes of this research are:

- a. To forecast production quantity
- b. To optimize total relevant cost of the integrated inventory model in dynamic JIT environment.

## 1.5 Research Benefits

The benefits of this research are:

- a. Enrich the knowledge about the role of JIT purchasing manufacturing systems, especially in the relationship between raw material suppliers and the company.
- b. The proposed integrated inventory model can be used to maintain a close and long term relationship between purchaser and vendor in JIT purchasing.
- c. Enrich the knowledge on the application of Artificial Intelligent in optimizing manufacturing system, especially in dynamic JIT environment.

## 1.6 Thesis Structure

The thesis structure is as follows:

### **CHAPTER II LITERATURE REVIEW**

Literature review provides information on previous studies. The objective is to seek the novelty of this research. Besides, it also explains the background theory.

### **CHAPTER III RESEARCH METHODOLOGY**

This chapter will present the research methodology, model development and the necessary data. The data is divided into 2 parts, namely primary and secondary data. Furthermore, this chapter will explain about the techniques of data collection and analysis. The final section of this chapter contains the framework of the research.

### **CHAPTER IV DATA COLLECTION AND PROCESSING**

This chapter presents information of data that have been collected during the research. It also contains problem solving using the proposed model or tools that are implemented in the data processing as well the analysis using the proposed model.

## **CHAPTER V DISCUSSION**

This chapter provides a discussion after data analysis. Furthermore, it also discuss about the result in order to see the ability of proposed model in order to overcome the problem.

## **CHAPTER VI CONCLUSION AND RECOMMENDATIONS**

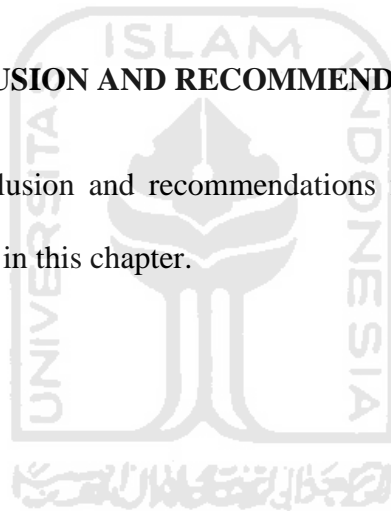
The conclusion and recommendations for further research will be described in this chapter.

## **REFERENCES**

## **APPENDIX**

Table

Figure



## CHAPTER II

### LITERATURE REVIEW

#### 2.1 Previous Research

Research issues concerning the philosophy of Just in Time (JIT) production system continue to get attention by many researchers. JIT philosophy in the issue of Supply Chain is also very interesting discussions such as issues concerning the integration of inventory in the JIT model that involves purchasing, lead-time, and quality improvement investment (Yang and Pan, 2004).

In the current Supply Chain Management (SCM) environment, buyers and vendors can both obtain greater benefit through strategic collaboration with each other (Stefan et al., 2004). Martinich (1997) mentioned that there are significant benefits of single building relationships towards their suppliers. Moreover, a close cooperation exists between suppliers and buyers to solve problems together. Thus, stability should be maintained long-term relationship between them. Since both buyers and suppliers may benefit from the negotiation, the two sides must then negotiate to determine how to divide the savings (Thomas and Griffin, 1996). Then, several studies have tried to create a model for integration of the buyer and suppliers.

Gunasekaran (1999) mentioned that the integrated model can contribute significantly to improve the vendor–purchaser relationship. The success and resulting performance of the integrated model is based upon the cooperation between the purchaser and supplier by having close location between them, make frequent deliveries, and are considered long-term partners. When establishing a long-term

relationship, it is important that the purchaser selects the vendors that have consistently exhibited high levels of quality and delivery reliability (Schonberger and Ansari 1984). Several researchers have shown that in integrated models, one partner's gain exceeds the other partner's loss. Thus, the net benefit can be shared by both parties in some equitable fashion (Goyal and Gupta 1989). Ha and Kim (1997) proposed a single-buyer and a single-vendor deterministic model with a single product integrated strategy that sends the first shipment as the product arrives at the transported quantity in a simple JIT environment. Pan and Yang (2004) extended Goyal's model (1988) by relaxing the production assumption and presented an integrated inventory model with controllable lead-time. Huang (2002) developed an integrated vendor-buyer cooperative inventory model for items with imperfect quality and assumed that the number of defective items followed a given probability density function. Pan and Yang (2004) developed an integrated inventory model in JIT purchasing involving demand and lead-time deterministic with quality improvement investment. Monika (2010) extended Pan and Yang (2004)'s model by changing the deterministic demand and lead-time to be probabilistic and uncertainty. The result show that the value of total relevant cost between supplier and buyer is always changing since the amount of demand is changed. Total relevant cost is includes cost of ordering/setup, holding, improving quality, accelerating cost of lead-time (crash cost of lead-time). It is important that total relevant cost should be minimized.

In the dynamic business, demand is always fluctuating and uncertainty (Ho, 1989). There are many forms of uncertainty and fuzziness condition that affect production processes. Many researchers have being applied fuzzy theory and techniques to develop and solve production problems. For example, Chen and Wang

(1996) fuzzified the demand, ordering cost, inventory cost and backorder cost into trapezoidal fuzzy numbers in an EOQ model with backorder consideration. Roy and Maiti (1997) presented a fuzzy EOQ model with demand-dependent unit cost under limited storage capacity. Lee and Yao (1998) fuzzified the demand quantity and production quantity per day with EPQ model. Yao et al. (2000) proposed an EOQ model where both order quantity and total demand were fuzzified as triangular fuzzy numbers. Chang (2004) applied fuzzy method for both imperfect quality items and annual demand to the EOQ model.

Since it is more appropriate to solve uncertainty problem, this research presents the models incorporated of fuzzy logic model to forecast the number of production when demand is uncertainty and integrated inventory of buyer and vendor. Integrated inventory model that used in this research using Pan and Yang (2004)'s model. The small error of prediction and minimum total relevant cost are parameters of optimize integrated inventory model. The Genetic Algorithm (GA) is used for this purpose. In order to justify the optimality of the solution provided by GA, there are two parameters will be used that are the premature convergent is not occurred in the searching process and the chromosomes can be improved in every generation therefore the hill climbing phenomenon is occurred.

## **2.2 Theoretical Background**

### **2.2.1 Just In Time (JIT)**

Just in Time (JIT) is the philosophy of the organization to reach a perfectness which are designed to produce or delivers goods or services as needed and minimize inventories, require major changes in traditional operating practices. Not only



inventories control issues, but also process management and scheduling issues are the way to bring up traditional manufacturing to a JIT system. JIT system focused on reducing inefficiency and unproductive time in the production process to improve continuously the process and the quality of the product services (Monden, 1995).

JIT systems are known by many different names, including zero inventory, synchronous manufacturing, lean production, stockless production, material as needed, and continuous flow manufacturing. Tersine (1994) described the differences of traditional manufacturing system and JIT system as follows:

Table 2.1 Characteristic conventional system vs JIT system

<b>Conventional</b>	<b>Just-in-Time</b>
Except some defect	Zero defects is necessary
Larger lot size for efficient	Ideal lot sizing is one
Rapid production is efficient	Line balancing is efficient
Inventory provides security	Safety stock is waste
Inventory is considered a smooth production	The presence of unwanted inventory
Inventory is asset	Should be no asset of inventory
Queue expanded	Queue must eliminate
Suppliers is the opposite	Suppliers is partners
Some sources give safety supplies	A little easier to control the source from suppliers
Breakdown maintenance is Enough	Preventive maintenance is essential
Long lead times are better	Short Lead time is better
Deterministic Setup time	Setup time should be close to zero
Management with the command	Management by consensus
Specialist workforce	Multi-function workforce

### 2.2.2 Just-In-Time Purchasing

JIT Purchasing system is the principles of no stock. JIT purchasing conducted accordance with needs, right quantity, best supplier, best design, and flexible. JIT purchasing is an integral part of the overall concept of JIT manufacturing.

JIT manufacturing system is based on the idea that "the inventory is the devil" because the scope is a quality problem with high costs to maintain it. Therefore, the

JIT system is set to eliminate the dependence on the inventory of finished goods, raw materials, and components. Elimination of inventory is forced manufacturing system able to providing the raw materials accordance to “Just In time” which assemble to finished good, then delivered accordance to “Just in Time” for sale.

JIT system is often pushed to build relationship with single vendor for specific spare parts. It is assumed that if produce in the small quantity, it will be produce high quality product and probably spend a little time to inspect in the receiving point (Zenz, 1994). Benefits of JIT purchasing system are shown in the Table 2.2

Table 2.2 The Effect of JIT purchasing practice

<b>Purchasing Activities</b>	<b>JIT Practice</b>	<b>Influence to Quality</b>
Lot Size	Purchase a small lot size with a high frequency delivery	detection and correction of defects
Supplier Evaluation	Evaluated the ability of suppliers in supply	Suppliers put the emphasis on product quality
Supplier Selection	Single source in a geographic area	Frequently visit technical worker to accelerate and improve quality understanding.
Product Specification	Fully only determine important product characteristics	Suppliers have a deeper wisdom about product design and manufacturing methods, which means the specifications are more likely to achieve
Commands / bidding	Remain with the same supplier; conduct informal value analysis to reduce the bid price, there is no repetition	Suppliers can afford the cost of long-term commitment to meet the quality requirements, and they become more aware of the need for genuine buyers
Acceptance Inspection	Vendor certified quality, acceptance inspection may be reduced and ultimately eliminated	Quality at the source (suppliers) are more effective and less costly
Paperwork	Reduce the formal system, and reduce the volume of paperwork	Much time is available for purchase

Source: Richard J. Schonberger and Ansari Abdolhossein. "Just-In-Time Purchasing Can Improve Quality," *Journal of Purchasing and Materials Management*, Spring 1984, pp, 2-7

There are some drawbacks associated with the JIT system. It necessitates a great deal of emphasis on quality, which may reduce purchasing ability to negotiate lowest possible prices. A balance between the two methodologies is necessary. JIT also reduces the number of competitors; ultimately it may be possible to raise prices because there is so little competition.

### **2.2.3 Lead Time**

Lead time is interval time between initiation and the completion of a production process. Lead-time can be interpreted differently depending on various items and / or activities that are included in the interpretation (Tersine, 1994). This occurred to certain item or operations refer to individually or collectively. Total time for the procurement of all raw materials and purchase components, process, test, and packaging the finished product is the production cycle time. Total manufacturing time required to perform all necessary operations exclusively in the factory (from the earliest time (earliest), to complete a final settlement (completion of last) is the manufacturing cycle time is the amount of each lead time.

Manufacturing cycle time is the elapsed time between orders and completion time spending items. This is the time consumed by jobs or orders in the manufacturing process. Tersine mention that manufacturing cycle time consists of the following five elements (Tersine, 1994) are described as follow:

1. Setup Time. Setup time is refer to the machine, raw material, preparing work station to operation

2. Process Time. Formation of production operation
3. Wait Time. Raw material waiting moved to the next location.
4. Move time. Transportation conducted from station to another stations.
5. Queue time. Raw material waiting cause there is order that still in process in a work station.

#### **2.2.4 Order/ Setup Cost**

Ordering cost is each time a firm places a new order, it incurs ordering cost, the cost of preparing a purchase order for a supplier or a production order for the shop. For the same item, the cost is the same, regardless of the order size: The purchasing agent must take the time to decide how much to order, select a supplier and negotiate terms. Time also is spent on paperwork, follow up, and receiving. In the case of a production order for manufactured item, a blueprint and routing instructions often must accompany the shop order (Krajewski and Ritzman, 1996).

Setup cost is the cost involved in changing over a machine to produce a different component or item is the setup cost. It includes labor and time to make the changeover, cleaning, and new tools or fixtures. Scrap or rework costs can be substantially higher at the start of the run. Setup cost also is independent of order size. Therefore, there is pressure to order a large supply of the component and hold it.

#### **2.2.5 Holding Cost**

The holding cost, synonymous with carrying cost, subsumes the costs associated with investing in inventory and maintaining the physical investment in storage. It incorporates such items as capital costs, taxes, insurance, handling, storage, shrinkage, obsolescence, and deterioration. Capital cost reflects lost earning power or opportunity

cost. If the funds were invested elsewhere, a return on the investment would be expected. Capital cost is a charge that accounts for this unreceived return. Many states treat inventories as taxable property; so the more you have, the higher the taxes. Insurance coverage requirements are dependent on the amount to be replaced if property is destroyed. Insurance premiums vary with the size of inventory investment. Obsolescence is the risk that an item will lose value because of shifts in styles or consumer preferences. Shrinkage is the decrease in inventory quantities over time from loss or theft. Deterioration means a change in properties due to age or environmental degradation. Many items are age-controlled and must be sold or used before an expiration date (e.g., food items, photographic materials, and pharmaceuticals). The usual simplifying assumption made in inventory management is that holding costs are proportional to the size of the inventory investment. On an annual basis, they most commonly range from 20 to 40% of the investment. In line with this assumption is the practice of establishing the holding cost of inventory items as a percentage of their dollar value (Tersine, 1994).

### **2.2.6 Crash Cost**

The Program Evaluation and Review Technique (PERT) and Critical Path Method (CPM) are the two most widely used techniques of management science. They are typically used in situations where managers have responsibilities for planning, scheduling, and controlling large projects that are composed of many activities performed by a variety of people in various work areas (Markland and Sweigart, 1987).

In PERT and CPM, the time associated with completing an activity in a network was fixed. In many projects, however, this situation may not be true, as the

manager may have the ability to assign more resources to an activity, thereby shortening it. For example, more workers or overtime may be used to shorten the time for a particular activity in a project. Decreasing the project activity time will usually be accompanied by an increase in the activity cost.

The term “crashing” refers to the shortening of project duration by “crashing” or “rushing” one or more of the critical project activities to completion in less than normal time. Extension of the typical critical path analysis for a project involves activity time-cost analysis and activity crashing. In performing a time-cost analysis, two types of costs associated with each activity are estimated. These costs are the normal-time cost and the crash-time cost, and are associated with two time estimates for each activity, the normal time and the crash time.

### **2.2.7 Mathematical Model**

Mathematical models may reside on a computer or simply on a pad of paper. However, they all share the common factor that a set of mathematical equations or logical relationships is developed to describe the real system. Parameters of the models, such as standard production times, time between machine failures, and batch sizes, are estimated from accounting and other data.

Mathematical models differ from physical models in their use of decision variables. We must have some intended use for the model, which revolves around variables that we can control. These become the decision variables of the model. The key to building useful models is to select the proper decision variables. This is closely related to problem definition and synthesis. As a general guide to determining the decision variables, the modeler should ask: What questions am I trying to answer?

Decision variables might be the number of machines needed or the set of tasks assigned to a machine.

Models are built for many purposes. Primary uses include the following (Askin and Standridge, 1993):

1. Optimization: finding the best values for decision variables
2. Performance prediction: checking potential plans and sensitivity
3. Control: aiding the selection of desired control rules
4. Insight-providing: better understanding of system
5. Justification: aiding in selling decisions and supporting viewpoints

### **2.2.8 Forecasting**

Forecasting is the act of predicting the future. Generally, forecasting can be divided into quantitative and qualitative approaches (Mun, 2006). Qualitative forecasting is used when little to no reliable historical, contemporaneous, or comparable data exists. Several qualitative methods exist such as the Delphi or expert opinion approach, management assumptions as well as market research or external data or polling and surveys for quantitative forecasting, the available data or data that needs to be forecasted can be divided into time-series, cross-sectional, or mixed panel.

Objective forecasting method is those in which the forecast is derived from an analysis of data, there are causal method and time series method (Nahmias, 2001). Causal is ones that use data from sources other than the series being predicted; that is, there may be other variables with values that are linked in some way is being forecasted. Time series method is one that uses only past value of the phenomenon we are predicting.

Mean Squared Error (MSE) is an absolute error measure that squares the errors (the difference between the actual historical data and the forecast-fitted data predicted by the model) to keep the positive and negative errors from cancelling each other out (Mun, 2006). This approach provides a penalty for large forecasting errors because it squares each. This is important since a technique that produces moderate errors may well be preferable to one that usually has small errors but occasionally yields extremely large ones (Hanke et al., 1998). The error of forecast must be smaller or less than 10 % (Gelder, 1984).

### **2.2.9 Fuzzy Logic**

Fuzzy logic is a branch of artificial intelligence systems (Artificial Intelligence) that emulates the human capability to think in the form of algorithms then executed by the engine. Fuzzy logic interprets the vague statement into a logical sense. Fuzzy logic system is a system with high accuracy to describe a problem; it can be used to solve a complex problem which requires a description in a human or intuitive thinking. As for how to use the controller must be the operator, the man who controls the system is qualitatively in the form of sentences in fuzzy or fuzzy numbers.

Uncertainty can be thought in an epistemological sense as being the inverse of information (Ross, 2004). Information about a particular engineering or scientific problem may be incomplete, imprecise, fragmentary, unreliable, vague, contradictory, or deficient in some other way (Klir and Yuan, 1995). When we acquire more and more information about a problem, we become less and less uncertain about its formulation and solution. Problems characterized by very little information are said to be complex, or not sufficiently known. These problems are imbued with a high degree of uncertainty. Uncertainty can be manifested in many forms: it can be fuzzy



(not sharp, unclear, imprecise, and approximate), it can be vague (not specific, amorphous), it can be ambiguous (too many choices, contradictory), it can be of the form of ignorance (dissonant, not knowing something), or it can be a form due to natural variability (conflicting, random, chaotic, and unpredictable).

## 1. Fuzzy Set

Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. Fuzzy sets provide a mathematical way to represent vagueness and fuzziness in humanistic systems (Ross, 2004). There are some functions could be used.

In the crisp set, the value of membership of an item  $x$  in a set  $A$  is often written with a  $\mu_A [x]$ , have two possibilities (Kusumadewi and Purnomo, 2004), namely:

- a. One (1) which means an item becomes a member in the set.
- b. Zero (0) which means an item don't becomes a member in the set.

There are two attributes in fuzzy set (Kusumadewi and Purnomo, 2004):

- a. Linguistics, the naming of a group representing a certain state or condition by using natural language, For example, cool, cold, warm, and hot.
- b. Numerical, that is a value (number) that shows the size of a variable such as:  
40, 25, 35

## 2. Membership Function

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.

a. Linier Representation

In linear representation, mapping the input to the degree of membership is described as a straight line. This is the simplest form and be a good choice for close to a concept that is unclear. There are two linier fuzzy set. First, increase the set started in the domain that has a value of zero degree of membership [0] to move right into the domain values that have a higher degree of membership.

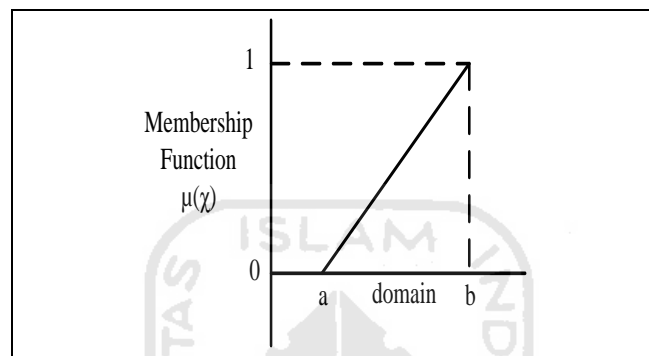


Figure 2.1 Linier representations up

Membership function:

$$\mu = \begin{cases} 0; & x \leq a \\ \frac{x - a}{b - a}; & a \leq x \leq b \\ 1; & x \geq b \end{cases} \quad (2.1)$$

Second is the opposite of the linier representation up. Straight line starting from domain values with the highest degree of membership on the left side, then move down to the domain values that have a lower degree of membership.

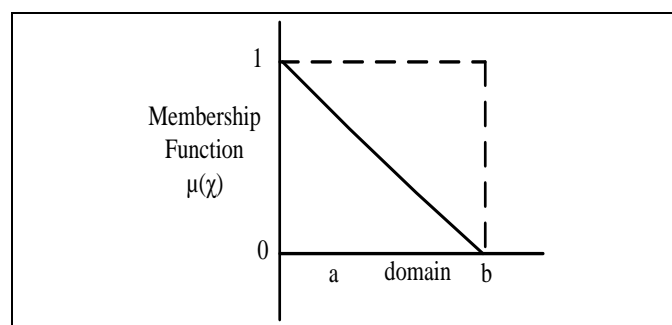


Figure 2.2 Linier Representation down

Membership function:

$$\mu = \begin{cases} (b-x)/(b-a); & a \leq x \leq b \\ 1; & x \leq a \end{cases} \quad (2.2)$$

b. Triangle Curve Representation

Triangle curve is a combination between the two lines (linear) as shown in the picture.

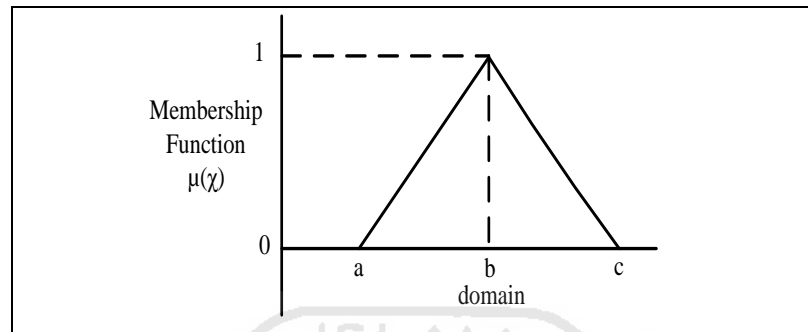


Figure 2.3 Triangle Curve Representations

Membership Function:

$$\mu = \begin{cases} 0; & x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a}; & a \leq x \leq b \\ \frac{c-x}{c-b}; & b \leq x \leq c \\ 0; & x \geq c \end{cases} \quad (2.3)$$

c. Trapezoid Curve Representation

Trapezoid curve is like a triangular shape, it's just that there are several points which have a membership value.

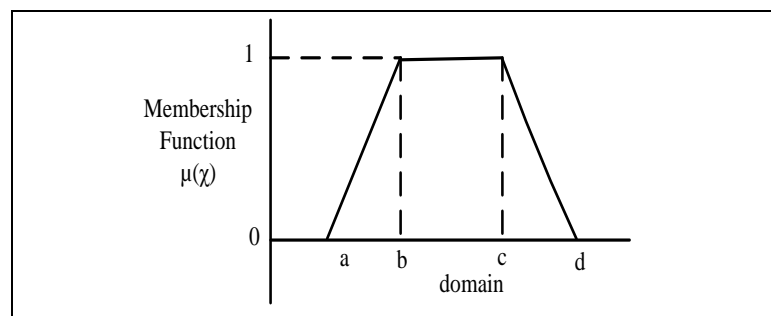


Figure 2.4 Trapezoid Curve Representations

Membership Function:

$$f(x; a, b, c, d) = \begin{cases} 0; & x \leq a \\ \frac{x-a}{b-a}; & a \leq x \leq b \\ 1; & b \leq x \leq c \\ \frac{d-x}{d-c}; & c \leq x \leq d \\ 0; & x \geq d \end{cases} \quad (2.4)$$

d. Shoulder Shaped Curve Representation

Areas located in the middle of a variable that is represented in the form of a triangle, on the right and left sides will move up and down (say: COOL move into COLD move into WARM and move into HOT). However, sometimes one side of the variable unchanged. For example, if the condition has reached HOT, rising temperatures will remain in the HOT condition. Fuzzy set 'shoulder shaped', not a triangle, used to end an area of fuzzy variables. Left shoulder move from right to wrong, as well as the right shoulder move from wrong to the right. Figure below shows the variable temperature with the shoulder area.

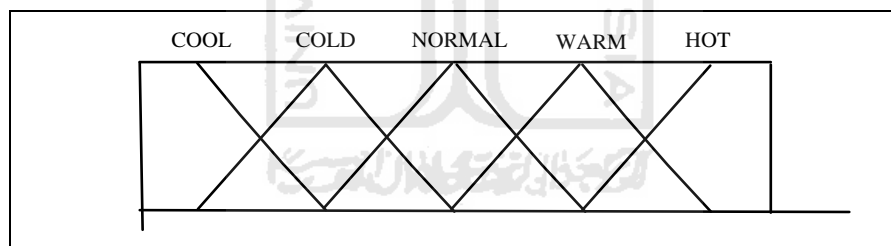


Figure 2.5 Shoulder Shaped Curve Representation for Variable Temperature

### 3. Sugeno Model

This reasoning is similar to the Mamdani reasoning, only the output (consequent) do not in fuzzy set form, but be constant or linear equation. There are two kinds of fuzzy sugeno model:

a. Fuzzy Sugeno Model Orde – Zero

General formulation:

$$\text{IF } (X_1 \text{ is } A_1) \cdot (X_2 \text{ is } A_2) \cdot (X_3 \text{ is } A_3) \cdot \dots \cdot (X_N \text{ is } A_N) \text{ THEN } z = k \quad (2.5)$$

With  $A_N$  is the fuzzy set to-N as antecedent, and  $k$  is the constant value as consequences.

b. Fuzzy Sugeno Model Order – One

$$\text{IF } (X_1 \text{ is } A_1) \cdot (X_2 \text{ is } A_2) \cdot (X_3 \text{ is } A_3) \cdot \dots \cdot (X_N \text{ is } A_N) \text{ THEN } z = P_1 \cdot X_1 + \dots + P_N \cdot X_N + q \quad (2.6)$$

With  $A_N$  is the fuzzy set to-N as antecedent, and  $p_i$  as the constant value to-i and  $q$  is the constant value in consequence.

There are four steps to obtain the output:

a. Formation of fuzzy set

Both the variable input and output variables are divided into one or fuzzy.

b. Application of implication function

The functions used are the implications MIN.

c. Rule evaluation

At this stage the system consists of several rules, the inference obtained from the collection and correlation between the rules. There are three methods used in conducting inference fuzzy system, ie: max, additive and probabilistic OR. At max method, the solution fuzzy set is obtained by taking the maximum value of the rule, then use it to modify the fuzzy, and put it into the output by using the OR operator (union). Generally, it can be written as follows.

$$\mu_{df}(x_i) \longleftarrow \max(\mu_{df}(x_i), \mu_{kf}(x_i)) \quad (2.7)$$

Most fuzzy rule-bases are implemented using a conjunctive relationship of the antecedents in the rules. This has been termed an intersection rule configuration (IRC) by (Combs and Andrews, 1998) because the inference process maps the intersection of antecedent fuzzy sets to output consequent fuzzy sets. This IRC is the general

exhaustive search of solutions that utilizes every possible combination of rules in determining an outcome (Ross, 2004).

$$R=I^n \text{ or } R=I_i I_{i+1} \quad (2.8)$$

Where:

R= the number rules

I= the number of linguistic labels for each input variable (assumed a constant for each variable).

n= the number of input variables

#### d. Defuzzyfication

Input from defuzzyfication process is a fuzzy set obtained from the composition rule of fuzzy rules, while the output is a fuzzy set of numbers in the domain. If given a fuzzy set in a certain range, it must be taken a certain crisp value as output.

### 2.2.10 Genetic Algorithm

Genetic Algorithm (GA) was developed by John Holland at the University of Michigan United States. GA has been applied in many fields. It used to solving optimization problem, despite that the GA has ability to solve except optimization. John Holland mentioned that each problem which form of adaptation (naturally or creation) can be formulated in genetic terminology. GA is simulation of the Darwin evolution and genetic operation of chromosome.

In genetic algorithm, search technique through the number of solution/settlement as known as population. Each individual in population called as chromosome. This chromosome is a solution that still in the form of symbol. The beginning population is formed randomly, while the next population is the result of chromosome evolution through iteration called as generation.

In each generation, chromosome through the evolution process by using measurement tool called as fitness function. Fitness function of a chromosome will show the quality of the chromosome in the population. The next generation known as child (offspring) formed by combination of two chromosome of present generation that acted as parent using crossover. Except crossover operator, a chromosome can be modified using mutation. The population of new generation that formed by selecting the fitness value from parent chromosome and fitness value from child chromosome, moreover rejecting the others chromosome, so the size of population will be constant. After through a few generations, so this algorithm will be convergent to the best chromosome.

There are three advantage of genetic algorithm application in optimization process are: (a) AG do not need many mathematical requisite in the settlement of optimization process. AG can be applied to the kind of objective function with a few limitation as well as linier or non linier form; (b) evolution operation of GA is very effective to observing global position by randomly; and (c) AG have flexibility to implemented efficiently to certain problematic.

### **2.2.11 Genetic Algorithm Procedures**

Genetic algorithm is very useful to solve complex optimization problem which difficult to solved using conventional method. As well as the evolution process in the nature, GA is consist of three operations are reproduction operation, crossover operation, and mutation operation. The operation can be seen as follow (Gen and Cheng, 1997):

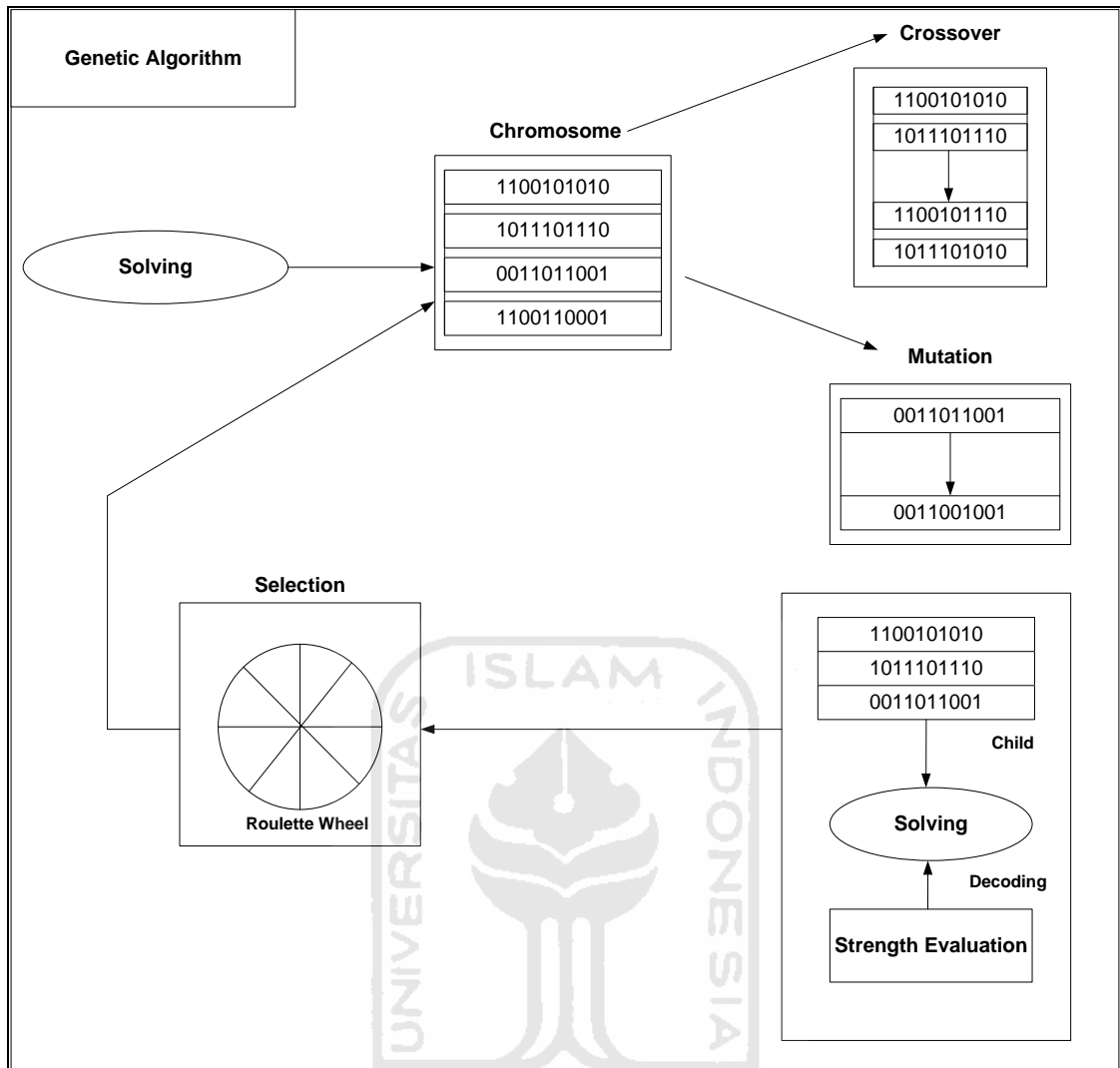


Figure 2.6 GA Structure

General structure of GA consist of this steps:

1. Evoking the first population randomly
2. Creating new generation by using three operation above repeatedly so obtained enough chromosome to create new generation as representation of new solution
3. Solution of evolution will evaluate each population with counting the fitness value for each chromosome until criteria stopped. If the criteria not fullfill yet, so it will create new generation by repeating the steps.



4. A few stopped criteria that generally used are:
  - a. Stopped at certain generation
  - b. Stopped after in a few generation successively, obtained the highest or lowest fitness value that is not changed.
  - c. Stopped if in n generation is not obtained the highest or lowest fitness value

### 2.2.12 The Comparasion Between Regular Optimization with GA

Generally, the algorithm to solve the optimization problem is one sequence step of calculation according to asymptote focus. Many classical optimization methods build one sequence of calculation based on highest power of objective function. The difference can be shown as follow:

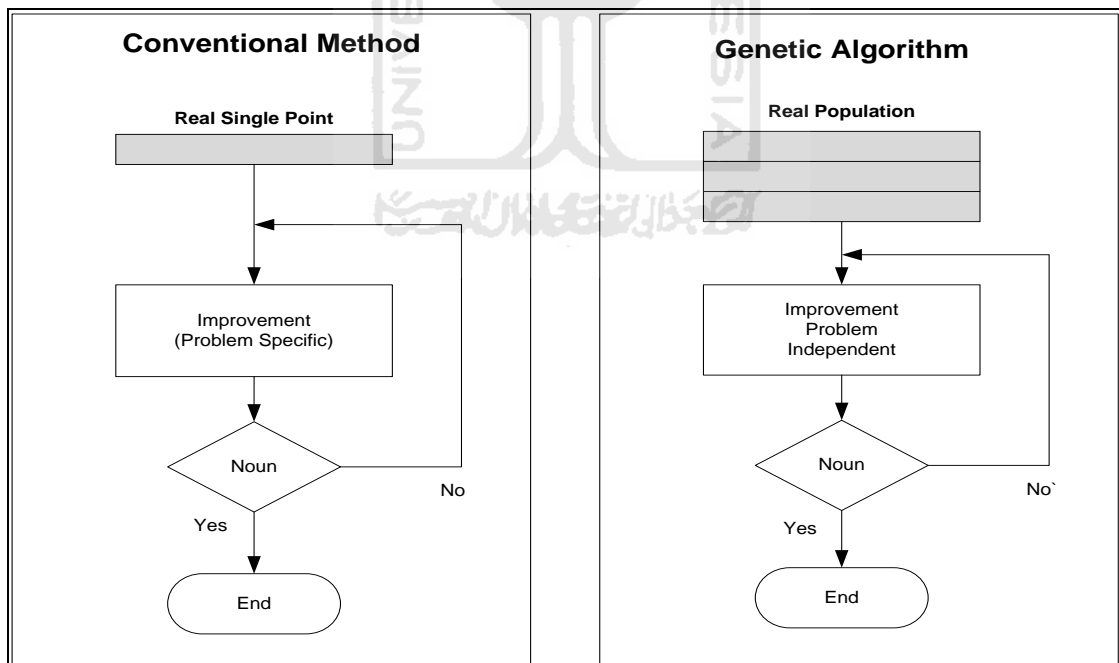


Figure 2.7 Comparasion between Conventional Method and Genetic Algorithm

The method used at a single point in the search space as depicted in Figure 2.7. This point is subsequently increased throughout the depth of the decline or rise

through the iteration gradually. Approach from one point to another is not beneficial or harmful if fall to point of local optimum.

GA forms a multidirectional search by maintaining a population that seeks completion. Population by population approach aims to avoid local optimum results. Simulation runs with the evolution of the population at each generation, relatively good progress is reproducible, and relatively poor resolution is discarded or ignored. GA uses probability transition rules, by choosing best chromosome to reproduced and disposes of the dead so that the search in the investigation space is increases (Gen and Cheng 1997; 2000).

### **2.2.13 Genetic Algorithm Components**

#### **A. Coding Technique**

Coding technique is how to coding the gen of chromosome. Usually, gen represents one variable. Gen can be represented in the form of real number, bit, rules list, mutation elements, program elements, or other representation that can be implemented to genetic operator. Coding technique is depending on the problem faced. As an example, code directly real number or integer.

Therefore, chromosome can be represented as:

1. String Bit: 11001, 10111
2. Array real number: 7.9, 9.7,-70
3. Mutation Element: E5, E8, E11
4. List Rule: R1, R2, R3
5. Element programs: genetic programming

#### **B. Evoking the Initialization Population**

Initialization population is process to form a number of individual randomly or through certain procedures. The sizes of population depend on the problem that want to solve and kind of genetic operator that will be implemented in the GA. If the size of population is determined, so generated initialization population is conducted. Conditions that must be met to demonstrate a solution should really be considered in the generation of each individual.

Some techniques in raising the initial population are:

### 1. Random Generator

The essence of this method is to involve the generation of random numbers for the value of each gene according to the chromosome representation used. If using a binary representation, one example of the use of random generator is to use the following formula for initial population:

$$IPOP = \text{round} \{ \text{random} (Nipop, Nbits) \} \quad (2.9)$$

IPOP where is the gene which will contain rounding of random numbers are generated as much Nipop (Total population) x Nbits (The number of genes in each chromosome).

### 2. Particular approach (entering particular value into the Gen)

This mode is by entering a specific value into the genes of the initial population is formed.

### 3. Gen Permutation

One way permutation of genes in the initial population is the use of Josephus permutations in combinatorial problems such as TSP.

## C. Selection

Selection is used to select individuals everywhere who will be chosen for crossover and mutation process. Selection is used to get a good potential parent. A good parent will produce good child/offspring. The higher the fitness value of an individual more likely to elect.

The first step taken in this selection is the search for fitness value. Fitness value will be used in subsequent stages of selection. Each individual in the container will receive probabilities reproductive selection depends on the objective value itself against objective values of all individuals in the container selection. There are two common methods of selection; Sorting Machine and Roulette Tournament.

#### **D. Crossover**

Cross Over is the operator of GA that involved two existing individual (parents) to form a new chromosome. Cross over to produce a new point in search space that is ready to be tested. This operation is not always done on all existing individual. Individuals selected at random to do with  $P_c$  crossing between 0.6 until 0.95. If the crossover is done, the value of the parent will be handed down to descendants.

The principle of these crossovers is to conduct operations (arithmetic exchanged) in the corresponding genes from parent to produce two new individuals. Crossover process is conducted on each individual with specified crossover probability. This crossover operator depends on the representation of chromosomes are made. Crossover operator will be described is as followed:

##### 1. Cross over one-point

Cross over one-point and many points are usually used for binary chromosome representation. At one point crossover, crossover position  $k$  ( $k = 1, 2, \dots, N-1$ ) with  $N$

= length of the chromosome were selected by random. Variables exchanged between the chromosomes at that point to produce a child. Illustrated in figure 2.14 one-point cross over with cross over probability is equal to 0.9.

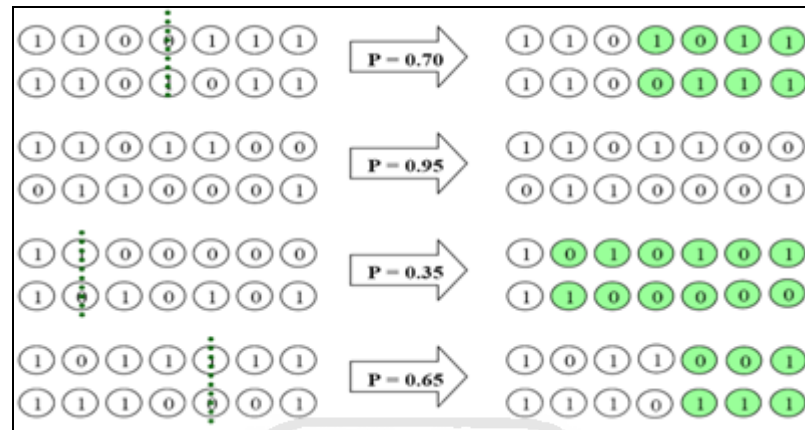


Figure 2.8 One-point cross over

## 2. Cross over with many points

On cross over many points, crossing position  $m$   $k_i$  ( $k = 1, 2, \dots, N-1$ ,  $i = 1, 2, \dots, m$ ) with  $N =$  length of the chromosome are selected randomly and are not allowed to have the same position, well sorted ride. Variables exchanged between the chromosomes at that point to produce a child. Figure 2.9 illustrated the cross over two points and figure 2.10 illustrated cross over more than two points.

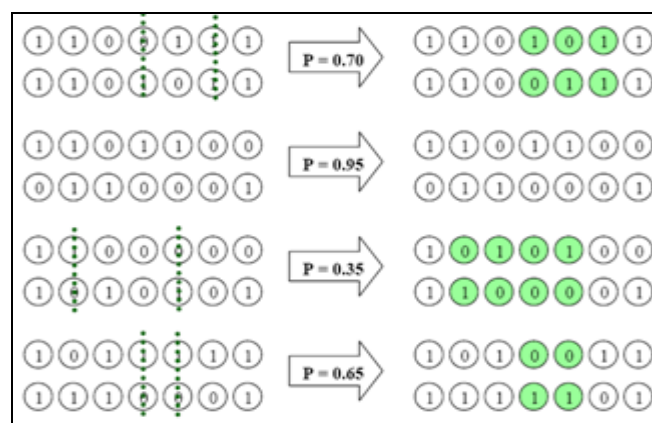


Figure 2.9 Cross over with two points

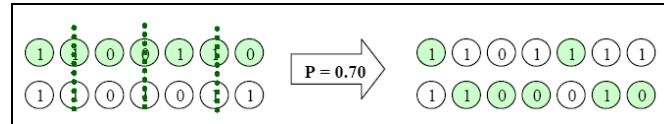


Figure 2.10 Cross over with more than two points

### 3. Arithmetic cross over

Arithmetic crossover is used for the representation of chromosomes in the form of float numbers (fractions). Cross over is done by determining the value of  $r$  as a random number greater than 0 and less than 1. It also determined the position of genes that do cross over using random numbers. Figure 2.11 illustrated the arithmetic crossover.

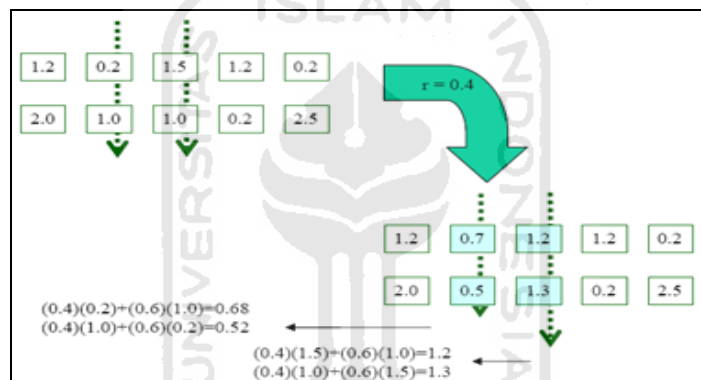


Figure 2.11 Arithmetic cross over illustration

### 4. Partial-Mapped Crossover to represent permutation chromosome

Partial-mapped crossover (PMX) is a modification of the formulation of two-point crossovers. The important thing from PMX is two-point crossovers with plus some additional procedures. PMX has the following working steps:

**Step 1:** specify two positions on the chromosomes with random rules. Substrings that are in these two positions are called mapping area.

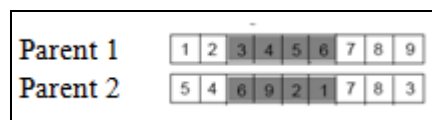


Figure 2.12 PMX steps 1

**Step 2:** switch the two substrings over parents to result the proto-child.

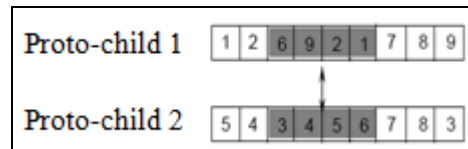


Figure 2.13 PMX steps 2

Step 3: specify the mapping relationship between the two mapping area.

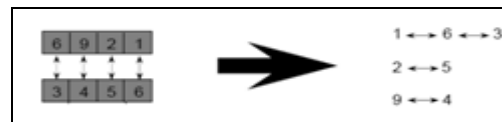


Figure 2.14 PMX steps 3

Step 4: Specify the offspring chromosomes mapping refers to the relationship.

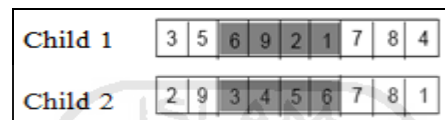


Figure 2.15 PMX steps 4

## E. Mutation

The next operator of genetic algorithm is a gene mutation. These operators serve to replace missing genes from the population due to selection processes that allow the re-emergence of genes that do not appear on the initialization population. Child chromosome mutated by adding random values are very small (the size of mutation steps) with a low probability. Opportunities mutation ( $P_m$ ) is defined as a percentage of the total number of genes in populations that experienced a mutation.

Opportunity to control the number of new gene mutations will be raised to be evaluated. If the chance of mutation is too small, many genes that may be useful not been evaluated. When the opportunity was too great mutation, it will be too much random noise, so the child will lose the resemblance of its mother, and also the algorithm lose the ability to learn and searching. Chromosome mutation results should be checked, whether still in the solution domain, and if necessary can be repaired.

Mutation as described as follows (Gen and Cheng, 1997)

3	4	5	1	2	4	7	8	10
3	4	5	1	8	4	7	8	10

Figure 2.16 Mutation process

## F. Generator v.1.0

Generator is a computer program that can help to solve a wide variety of problems, whether they are complex or simple. It is designed to interact with Microsoft Excel worksheets. Basically, the problem is defined in Excel worksheet then connected to the generator to find a solution. The Generator is able to maximize profits, minimize costs, or solve equations. Excel worksheet has to have input variables and a single output expression which describes the quality of a solution (eg., cost, profit, MSE, etc.).

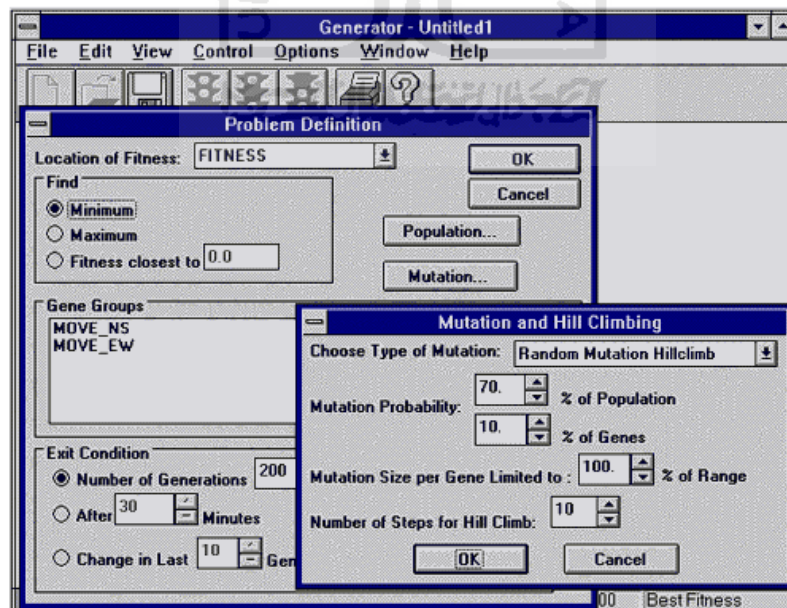


Figure 2.17 Display of Generator v1.0



## CHAPTER III

### RESEARCH METHODOLOGY

This chapter explains the research methodology such as research object definition, mathematical formulation, model validation, data requirement, analysis data, analysis tool, and research frameworks. Detail steps of the research which is arranged in sub-chapters as below:

#### 3.1 Research Object

The study was conducted at PT. Aseli Dagadu Djogdja (PT.ADD) and PT. Narigus. This research is focused on development of integrated inventory model based on determination of number production to meet uncertainty in demand.

#### 3.2 Mathematical Model

##### 3.2.1 Mathematical Notation

##### 1. Mathematical Fuzzy Logic

$D$  : Number of demand

$I$  : Inventory level

$TP$  : Number of Production

$R$  : Fuzzy rule

$a$  : weight of  $D$

$b$  : weight of  $I$

$c$  : constant

$MSE$  : Mean Square Error

$PME$  : Percentage Mean Error

$R(r)$  : Fuzzy rule in number  $r$

## 2. Integrated Inventory Model

### a. Variable

$Q^*$  = Order quantity.

$m^*$  = number of deliveries.

$\theta^*$  = Probability of process being out of control.

$L^*$  = Lead time.

### b. Parameters

$D$  = Demand per year.

$P$  = Production rate per year

$A$  = Purchaser's ordering cost per order.

$S$  = Vendor's setup cost per setup.

$C_V$  = Unit production cost paid by the vendor.

$C_P$  = Unit purchase cost paid by the purchaser.

$r$  = Annual inventory holding cost per dollar invested in stocks.

$i$  = The fractional per unit time opportunity cost of capital.

$a_i$  = Minimum duration.

$b_i$  = Normal duration.

$c_i$  = Crashing cost per unit time.

$R(L)$  = Lead time crashing cost per cycle.

$g$  = Cost of replacing a defective unit.

$k$  = Safety factor.

$\sigma$  = Standard deviation.

$x$  = Lead time demand

$\bar{xL}$  = Mean of expected demand during lead-time

$I$  = Inventory

$\pi_x$  = Back-order price discount offered by the supplier per unit,  $0 \leq \pi_x \leq \pi_0$

$\pi_0$  = Gross marginal profit per unit

$\delta$  = Back-order parameters,  $0 \leq \delta \leq 1$

Logarithmic investment function:

$$q(\theta) = q \ln(\theta_0/\theta)$$

$\theta_0$  = Current probability that the production can go out of control.

$$q = 1/\xi$$

$\xi$  = Percentage decrease in  $\theta$  per dollar increase in  $q(\theta)$ .

Number of setup:

$$C_p = \text{setup cost (\$/setup)}$$

$$C_h = \text{holding cost (\$/year)}$$

$$r = \text{demand (unit/year)}$$

The assumptions made in the paper are as follow:

1. The product is manufactured with a finite production rate  $P$ , and  $P > D$ .
2. The demand  $X$  during the lead-time  $L$  follows a normal distribution with mean  $DL$  and standard deviation  $\sigma$ .
3. The reorder point (ROP) equals the sum of the expected demand during lead time and the safety stock, that is, the reorder point equals  $ROP = \mu L + k\sigma\sqrt{L}$ , where  $k$  is known as the safety factor.
4. Inventory is continuously reviewed.

The out-of-control probability  $\theta$  is a continuous decision variable, and is described by a logarithmic investment function. The quality improvement and capital investment is represented by  $q(\theta) = q \ln(\theta_0/\theta)$  for  $0 < \theta \leq \theta_0$ , where  $\theta_0$  is the current probability that the production process can go out of control, and  $q = 1/\xi$ , with  $\xi$  denoting the percentage decrease in  $\theta$  per dollar increase in  $q(\theta)$ .

### 3. Objective Function/Fitness Function

$W$ =Weight

$A$ =Mean Square Error (MSE)

$B$ =Total Relevant Cost (TRC)

#### 3.2.2 Fuzzy Logic Model

To construct solution of Fuzzy Logic model will be described is as follow:

##### 1. Define Input and Output Variable

This research concerns on causal forecasting using mathematical fuzzy logic. The input variables to be analyzed are number of demand ( $D$ ) and inventory level ( $I$ ). The output variable is the total production quantity ( $TP$ ) which will be obtained through forecasting technique by considering the input variables.

##### 2. Fuzzy Set and Membership Function

Fuzzy set of ( $D$ ) and ( $I$ ) is shown in shown in figure 3.1 and 3.2 respectively.

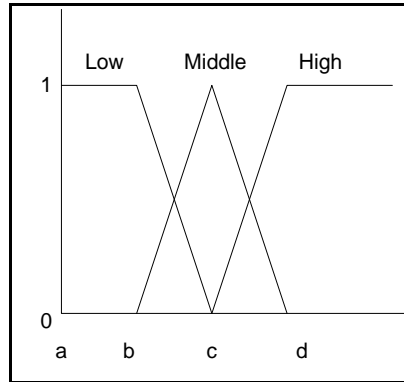


Figure 3.1 Representation of (D)

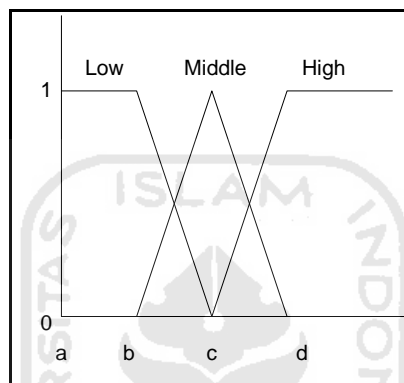


Figure 3.2 Representation of (I)

Membership function will described is as follow:

$$\mu_{A \text{ Low}}(x) = \begin{cases} 0; & x \geq c \\ 1; & x \leq b \\ \frac{c-x}{c-b}; & b \leq x \leq c \end{cases} \quad (3.1)$$

$$\mu_{A \text{ Middle}}(x) = \begin{cases} 0; & x \leq b \\ \frac{x-b}{c-b}; & b \leq x \leq c \\ \frac{d-x}{d-c}; & c \leq x \leq d \\ 0; & x \geq d \end{cases} \quad (3.2)$$

$$\mu_{A \text{ High}}(x) = \begin{cases} 0; & x \leq c \\ \frac{x-c}{d-c}; & c \leq x \leq d \\ 1; & x \geq d \end{cases} \quad (3.3)$$

### 3. Fuzzy Rule

The Fuzzy inference system to be used is Sugeno system and general form of the Fuzzy rules is shown in Equation 4.7.

$$R_i = \text{IF } D \text{ is } \tilde{D} \text{ AND } I \text{ is } \tilde{I} \text{ THEN } TP = a_i D + b_i I + c_i, \forall i, i = 1, \dots, 9 \quad (3.4)$$

Where :  $\tilde{D}$  = Fuzzy universe of discourse of  $D$

$\tilde{I}$  = Fuzzy universe of discourse of  $I$

$a$  = weight of  $D$

$b$  = weight of  $I$

$c$  = constant

$i$  = rule index

#### 4. Defuzzification

Defuzzification is conducted using the Centroid method. This method is most simple, prevalent and physically appealing of all the defuzzification methods. The one of defuzzification methods is weighted average method. It is valid for symmetrical output membership functions, but have less computationally intensive. The crisp value of predicted production could be modeled is as follows:

$$P \text{ prediction} = \frac{\sum_{i=1}^r \mu_A(x) x (TP) R_i}{\sum_{i=1}^r \mu_A(x)} \quad (3.5)$$

#### 5. Forecasting Error Measurement

Mean square Error is formulated as follow:

$$MSE = \frac{\sum_{t=1}^n (TP_t - TP'_t)^2}{n} \quad (3.6)$$

Percentages mean Error is formulated as follow:

$$PME = \frac{\sum_{t=1}^n [(TP_t - TP'_t)]}{n} \times 100\% \quad (3.7)$$

### 3.2.3 A Basic Model Integrated Inventory

The expected annual total cost of an integrated inventory model with normally distributed lead-time demand for minimizing the sum of the ordering cost, holding cost and crashing cost can be expressed is as follow (Pan and Yang 2002):

$$\begin{aligned}
 JTEC(Q, L, m) &= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} r \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) C_V + C_P \right] + r C_p k \sigma \sqrt{L} \\
 &= \frac{D}{Q} \left[ A + \frac{S}{m} + \left\{ c_i (L_{i-1} - L) + \sum_{j=1}^{i-1} c_j (b_j - a_j) \right\} \right] \\
 &\quad + \frac{Q}{2} r \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) C_V + C_P \right] + r C_p k \sigma \sqrt{L} \quad (3.8)
 \end{aligned}$$

where  $m$  is an integer representing the number of shipments of the item delivered to the purchaser, and  $a_i$ ,  $b_i$ ,  $c_i$  are the minimum duration, normal duration and crashing cost per unit time, respectively, of the  $i$ th component of lead time. Let  $\sum_{i=1}^n a_i \leq L \leq \sum_{i=1}^n b_i$ , and let  $L_i$  be the length of the  $i$ th component of the lead time crashed to its minimum duration. Then  $L_i$  can be expressed as  $L_i = \sum_{i=1}^n b_i - \sum_{j=1}^i (b_j - a_j)$ ,  $i = 1, 2, \dots, n$ . Also let  $R(L)$  denote the lead-time crashing cost per cycle for a given  $L \in [L_i, L_{i-1}]$ , and  $R(L) = c_i [L_{i-1} - L] + \sum_{j=1}^{i-1} c_j (b_j - a_j)$ .

In order to include the essence of an imperfect production process, consider the assumption made in the model proposed by Porteus (1986). The integrated inventory model is designed for vendor production situations in which, once an order is placed, production begins and a constant number of units is added to the inventory each day until the production run has been completed.

The vendor produces the item in the quantity  $mQ$  with a given probability of  $\theta$  that the process can go out of control. Porteus (1986) suggested the expected number of defective items in a run of size  $mQ$  can be evaluated as  $m^2Q^2\theta/2$ . Suppose  $g$  is the cost of replacing a defective unit, and the production quantity for the supplier in a lot of  $mQ$ . Then its expected defective cost per year is given by  $gmQD\theta/2$ .

Hence, the total expected annual cost incorporating the defective cost per year can be represented by

$$TC(Q, m, L) = JTEC(Q, m, L) + \frac{gmQD\theta}{2} \quad (3.9)$$

### 3.2.4 Investment in Quality Improvement

Based on equation (3.9), this research wish to study the effect of investment on quality improvement. Consequently, the objective of the integrated model is to minimize the sum of the ordering/setup cost, holding cost, quality improvement and crashing cost by simultaneously determining the optimal values of  $Q$ ,  $m$ ,  $\theta$  and  $L$ , subject to the constraint that  $0 < \theta \leq \theta_0$ . Thus, the total relevant cost per year is

$$\begin{aligned} TRC(Q, m, \theta, L) &= TC(Q, m, L) + iq \ln \frac{\theta_0}{\theta} \\ &= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_V + rC_P + gmD\theta \right] + rC_P k\sigma\sqrt{L} + \\ & \quad iq \ln \frac{\theta_0}{\theta} \end{aligned} \quad (3.10)$$

for  $0 < \theta \leq \theta_0$ , where  $i$  is the fractional opportunity cost of capital per unit time.

Therefore, the problem under study can be formulated as the following nonlinear programming model:



Minimize  $TRC(Q, m, \theta, L)$

$$= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_v + rC_p + gmD\theta \right] + rC_p k \sigma \sqrt{L} + iq \ln \frac{\theta_0}{\theta} \quad (3.11)$$

Subject to  $0 < \theta \leq \theta_0$

In order to find the minimum cost for this non-linear programming problem, ignore the constraint  $0 < \theta \leq \theta_0$  for the moment and minimize the total relevant cost function over  $Q$ ,  $\theta$  and  $L$  with classical optimization techniques by taking the first partial derivatives of  $TRC(Q, m, \theta, L)$  with respect to  $Q$ ,  $\theta$  and  $L$  as follows:

$$\frac{\partial TRC(Q, m, \theta, L)}{\partial Q} = -\frac{D}{Q^2} \left( A + \frac{S}{m} + R(L) \right) + \frac{1}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_v + rC_p + gmD\theta \right] \quad (3.12)$$

$$\frac{\partial TRC(Q, m, \theta, L)}{\partial \theta} = \frac{gmDQ}{2} - \frac{iq}{\theta} \quad (3.13)$$

$$\frac{\partial TRC(Q, m, \theta, L)}{\partial L} = -c_i \frac{D}{Q} + \frac{1}{2} rC_p k \sigma L^{-\frac{1}{2}} \quad (3.14)$$

However, for fixed values of  $Q$  and  $\theta$ ,  $TRC(Q, m, \theta, L)$  is concave in  $L \in [L_i, L_{i-1}]$ , because

$$\frac{\partial^2 TRC(Q, m, \theta, L)}{\partial L^2} = -\frac{r}{4} C_p k \sigma L^{-\frac{3}{2}} < 0$$

Therefore, for fixed  $Q$  and  $\theta$ , the minimum joint total expected annual cost will occur at the end-points of the interval. On the other hand, for a given value of  $L \in [L_i, L_{i-1}]$ , setting equations (3.12) and (3.13) equal to zero and solving for  $Q$  and  $\theta$ , it follows that

$$Q = \left[ \frac{2D(A + S/m + R(L))}{r(C_V(m(1 - D/P) - 1 + 2D/P) + C_P) + gmD\theta} \right]^{\frac{1}{2}} \quad L \in [L_i, L_{i-1}] \quad (3.15)$$

and

$$\theta = \frac{2iq}{gmDQ} \quad (3.16)$$

Theoretically, for fixed  $L \in [L_i, L_{i-1}]$ , one can find the optimal values of  $Q^*$  and  $\theta^*$  from (3.15) and (3.16). In addition, for fixed  $L \in [L_i, L_{i-1}]$ , the Hessian matrix of  $TRC(Q, m, \theta, L)$  is positive definite at  $Q^*$  and  $\theta^*$ . The proof is shown in the appendix.

For a particular value of  $m$ , the total relevant annual cost is described by

$$TRC(m) = \left[ 2D \left( A + \frac{S}{m_{R(L)}} \right) \left( rC_V \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) + rC_P + gmD\theta \right) \right]^{\frac{1}{2}} + rC_P k \sigma \sqrt{L} + iq \ln \frac{\theta_0}{\theta} \quad (3.17)$$

Ignore the terms that are independent of  $m$ , and take the square of (3.16); then, minimizing  $TRC(m)$  is equivalent to minimizing

$$\begin{aligned} & (TRC(m))^2 \\ &= 2D \left( A + \frac{S}{m_{R(L)}} \right) \left( rC_V \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) + rC_P + gmD\theta \right) \\ &= 2D \left[ (A + R(L)) \left( rC_P - \left( 1 - \frac{2D}{P} \right) rC_V \right) + S \left( rC_V \left( 1 - \frac{D}{P} \right) + gD\theta \right) \right] \end{aligned}$$

$$+m(A + R(L))\left(rC_v\left(1 - \frac{D}{P}\right) + gD\theta\right) + \frac{S}{m}\left(rC_p - \left(1 - \frac{2D}{P}\right)rC_v\right)\right]$$

Once again, ignoring the terms that are independent of  $m$ , the minimization of the problem can be reduced to that of minimizing

$$Z(m) = m(A + R(L))\left(rC_v\left(1 - \frac{D}{P}\right) + gD\theta\right) + \frac{S}{m}\left(rC_p - \left(1 - \frac{2D}{P}\right)rC_v\right) \quad (3.18)$$

The optimal value of  $m = m^*$  is obtained when

$$Z(m^*) \leq Z(m^* - 1) \quad \text{and} \quad Z(m^*) \leq Z(m^* + 1) \quad (3.19)$$

Substituting relevant values in (3.18), the following condition holds:

$$m^*(m^* - 1) \leq \frac{S(rC_p - (1 - 2D/P)rC_v)}{(A + R(L))(rC_v(1 - D/P) + gD\theta)} \leq m^*(m^* + 1) \quad (3.20)$$

Hence, for fixed  $L \in [L_i, L_{i-1}]$ , when the constraint  $0 < \theta \leq \theta_0$  is ignored, one can find the optimal values of  $Q^*$ ,  $m^*$  and  $\theta^*$  such that the annual total relevant cost reaches a minimum.

The following procedure is constructed to find optimal values of  $Q$ ,  $m$ ,  $\theta$  and  $L$  for the problem under investigation.

Step 1. For each  $L_i$ ,  $i = 1, 2, \dots, n$ , set  $\theta_i = \theta_0$  and perform (i)–(iii):

- (i) Substitute  $\theta_i$  into equation (3.20) to find  $m_i$ , and use  $\theta_i$  and  $m_i$  to compute  $Q_i$  using equation (3.15).
- (ii) Use  $Q_i$  and  $m_i$  to determine  $\theta_i$  from equation (3.16).
- (iii) Repeat (i)–(ii) until no change occurs in the values of  $Q_i$ ,  $m_i$  and  $\theta_i$ . Denote these solutions by  $Q_i^*$ ,  $m_i^*$  and  $\theta_i^*$ , respectively.

Step 2. If  $\theta_i^* \leq \theta_0$ , then the solution found in step 1 is optimal for the given  $L_i$ ; so use equation (3.11) to compute  $TRC(Q_i^*, m_i^*, \theta_i^*, L_i)$ , for  $i = 0, 1, \dots, n$ , and go to step 4.

Step 3. If  $\theta_i^* > \theta_0$ , set  $\theta_i^* = \theta_0$  for the given  $L_i$ , then substitute  $\theta_i^*$  into equation (3.20) to compute  $m_i^*$ , and use  $\theta_i^*$  and  $m_i^*$  to determine  $Q_i^*$  from equation (3.15); so use equation (3.11) to calculate  $TRC(Q_i^*, m_i^*, \theta_i^*, L_i)$ , for  $i = 0, 1, \dots, n$ .

Step 4. Set  $TRC(Q_s, m_s, \theta_s, L_s) = \min_{i=0,1,\dots,n} \{ TRC(Q_i^*, m_i^*, \theta_i^*, L_i) \}$ . Then  $TRC(Q_s, m_s, \theta_s, L_s)$  is a set of optimal solutions.

### 3.2.5 Fractional per Unit Time Opportunity Cost of Capital

$$i = \frac{\pi_x}{\pi_0} \times \delta \quad (3.21)$$

### 3.2.6 Objective Function

$$\text{Objective Function} = \frac{AxW1 + BxW2}{W1 + W2} \quad (3.22)$$

### 3.2.7 Genetic Algorithm

This research is focused on optimizing the model by using artificial intelligence optimization tools is Genetic Algorithm (GA). The GA has calculation procedures that able to adapt survival of the fitness to find the optimal solution. GA procedure begins a random population solution. Each individual in the population called chromosome, which represent a solution. Usually, the chromosome is represented as a string symbol that normally binary shaped but not always. This chromosome is to regenerate through iterations sequence. During regeneration, chromosome is evaluated using a measure called fitness value or objective function (Goldberg, 1989).

The GA has been proven as an effective optimization tool that can give optimal or near optimal solution, efficient manner. Furthermore, GA does not require many assumptions in solving the objective function like any other optimization techniques (Lee, CY, et al., 1997). The steps to run the GA is described as follow:

### **1. Initialization**

The GA requires a group of initial solutions. There are two ways of forming this initial population. The first consist of using randomly produced solution created by a random number generator. The second method employs a prior knowledge about the given assumptions (Pham and Karaboga, 2000). Each individual in the population called chromosome. This chromosome is to regenerate through iterations sequence. During regeneration, chromosome is evaluated using a measure called fitness value or objective function (Goldberg, 1989). The fitness evaluation unit acts an interface between the GA and optimization problem. After forming initial population, the representation of chromosome is needed as the parameter to be optimized. The parameters usually represented in a string form. The representation give major impact on the performance of the GA. Different representation schemes might causes different performances in terms of accuracy (Pham and Karaboga, 2000). Here is the example of representation of chromosome is shown in figure 3.3.

Demand	500	1000	1000								
Inventory	50	300	350								
Rule Weight	1.2	1.3	1.1								
Objective Weight	0.9	1.9									
Chromosome	500	1000	1000	50	300	350	1.2	1.3	1.1	0.9	1.9

Figure 3.3 Representation of Chromosome

## 2. Genetic Operator

There are three common genetic operators: crossover, mutation, and selection (Pham and Karaboga, 2000). The genetic operator is described as follow:

### a. Selection

The purpose of the selection procedure is to reproduce more copies of individual whose fitness values are higher than those whose fitness values are low. The selection procedure has a significant influence on driving the search towards a promising area and finding good solutions in a short time. However, the diversity of the population must be maintained to avoid premature convergence and to reach the global optimal solution. Proportional selection is usually called “roulette wheel” selection since its mechanism is reminiscent of the operation of a roulette wheel. Fitness values of individuals represent the widths of slots on the wheel. After a random spinning of the wheel to select an individual for the next generation, individuals in slots with the large widths representing high fitness values will have a higher chance to be selected.

### b. Crossover

The crossover is used to create two new individual (children) from two existing individuals (parents) picked from the current population by the selection operator. Some common crossover operations are one point crossover and two cut point crossover. One point crossover is simplest crossover operation. Two individuals are randomly selected as parents from the pool of individuals formed by the selection procedure and cut a randomly chosen point. The tails, which are the parts after cutting point, are swapped and two new individuals (children or offspring) are produced.

### **c. Mutation**

All individuals in the population are checked bit by bit and the bit values are randomly reversed according to a specified rate. Unlike crossover, this is a monadic operation. That is, a child string is produced from a single parent string. The mutation helps the GA avoid premature convergence and find the global optimal solution.

### **3. Termination**

Termination is the criterion by which the genetic algorithm decides whether to continue searching or stop the search. Each of the enabled termination criterion is checked after each generation to see if it is time to stop. A termination method that stops the evolution when the fitness value is deemed as converged.

### **3.3 Model Validation**

Validation of the model conducted is using dimension analysis. This action is necessary in order to provide a consistency of unit. After the unit is stated as consistent, subsequently the model is accepted and significant. In other word, the model utilized in this research is valid.

## 1. Dimension Analysis

a. Number of deliveries ( $m$ )

$$\begin{aligned}
 m &= \frac{S(rC_p - (1 - 2D/P)rC_v)}{(A + R(L))(rC_v(1 - D/P) + gD\theta)} \\
 &= \frac{\$/_{setup} \left( \frac{\$/_{year}}{\$/_{unit}} \times \$/_{unit} - \left( 1 - 2 \frac{\$/_{year}}{\$/_{unit}} \right) \times \frac{\$/_{year}}{\$/_{unit}} \times \$/_{unit} \right)}{\left( \$/_{order} + \$/_{unit} \right) \left( \frac{\$/_{year}}{\$/_{unit}} \times \$/_{unit} \left( 1 - \frac{\$/_{year}}{\$/_{unit}} \right) + \left( \$/_{unit} \times \text{unit}/\text{year} \right) \right)} \\
 &= \frac{\$/_{setup} \times \$/_{year}}{\left( \$/_{order} + \$/_{unit} \right) \times \left( \$/_{year} \right)} \\
 &= \$/_{setup} \times \text{unit}/\$
 \end{aligned}$$

$m = \text{constant}$

b. Order quantity ( $Q$ )

$$\begin{aligned}
 Q &= \left[ \frac{2D(A + S/m + R(L))}{r(C_v(m(1 - D/P) - 1 + 2D/P) + C_p) + gmD\theta} \right]^{\frac{1}{2}} \\
 &= \left[ \frac{2 \text{unit}/\text{year} \left( \$/_{order} + \frac{\$/_{setup}}{m} + \$/_{unit} \right)}{\text{unit}/\text{year} \left( \$/_{unit} \left( m \left( 1 - \frac{\text{unit}/\text{year}}{\$/_{unit}} \right) - 1 + 2 \frac{\text{unit}/\text{year}}{\$/_{unit}} \right) + \$/_{unit} \right) + \$/_{unit} \cdot m \cdot \text{unit}/\text{year}} \right]^{\frac{1}{2}} \\
 &= \left[ \frac{\text{unit}/\text{year} \cdot \$/_{unit}}{\text{unit}/\text{year} \cdot \left( \$ + \$/_{unit} \right) + \$/_{year} \cdot \text{unit}} \right]^{\frac{1}{2}}
 \end{aligned}$$



$$= \frac{\$/\text{year}}{\$/\text{year} \cdot \text{unit}}$$

$$Q = \text{unit}$$

c. Out-of-control probability ( $\theta$ )

$$\theta = \frac{2iq}{gmDQ}$$

$$= \frac{2 \cdot \$/\text{year}}{\$/\text{unit} \cdot m \cdot \text{unit}/\text{year} \cdot \text{unit}}$$

$$\theta = \text{constant}$$

d. Total relevant cost ( $TRC$ )

Minimize  $TRC(Q, m, \theta, L)$

$$= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_V + rC_P + gmD\theta \right] + rC_P k \sigma \sqrt{L} + iq \ln \frac{\theta_0}{\theta}$$

$$= \frac{\text{unit}/\text{year}}{\text{unit}} \left[ \$/\text{order} + \frac{\$/\text{setup}}{m} + \$/\text{unit} \right] + \frac{\text{unit}}{2} \left[ \left( m \left( 1 - \frac{\text{unit}/\text{year}}{\text{unit}/\text{year}} \right) - 1 + \frac{2 \cdot \text{unit}/\text{year}}{\text{unit}/\text{year}} \right) \cdot \text{unit}/\text{year} \cdot \$/\text{unit} + \text{unit}/\text{year} \cdot \$/\text{unit} + \$/\text{unit} \cdot m \cdot \text{unit}/\text{year} \right] + \text{unit}/\text{year} \cdot \$/\text{unit} \cdot \text{unit}/\text{week} \cdot (\text{day})^{\frac{1}{2}} + \$/\text{year}$$

$$= \$/\text{year} + \frac{\text{unit}}{2} \left[ m \cdot \text{unit}/\text{year} \cdot \$/\text{unit} + \$/\text{year} \right] + \$/\text{year} + \$/\text{year}$$

$$TRC = \$/\text{year}$$

### 3.4 Data Requirement

This research uses secondary data obtained from previous researcher's data. The data is concern about the relationships of a single vendor and a single purchaser. The research uses data about production planning and inventory of PT.ADD and PT. Narigus. The data is described as follow:

#### A. PT.ADD

1. Data about actual demand
2. Lead time data
3. Purchase's order cost element
4. Reorder point (*ROP*)

#### B. PT. Narigus

1. Actual inventory and production
2. Setup cost of PT. Narigus,
3. Production cost
4. Primary holding cost
5. Percentage Decrease in  $\theta$  and Rupiah Increase in  $q(\theta)$
6. Back order and gross marginal data
7. Defective unit data

### 3.5 Data Analysis

Data analysis concerns to optimize the integrated inventory model based on optimized fuzzy logic to conduct forecasting in dynamic business environment and minimum total relevant cost of buyer and vendor. The parameters of optimize integrated model

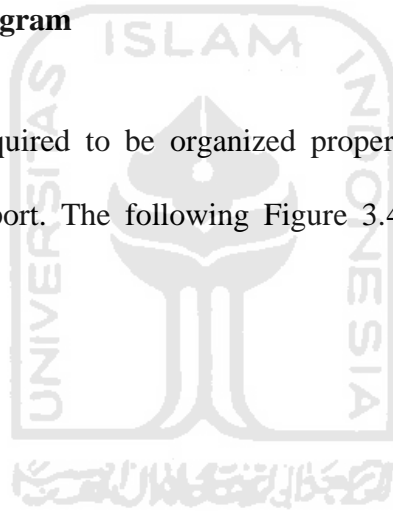
by reducing the error of forecast and minimize total relevant cost using genetic algorithm.

### **3.6 Analysis Tool**

The model applied in data analysis is processed using spreadsheet in Microsoft Excel<sup>®</sup>. The problem formulation that already processed using spreadsheet in Microsoft Excel<sup>®</sup>, then connected to the generator GA NLI-Gen<sup>®</sup> to optimize the parameters based on Genetic Algorithm Optimization.

### **3.7 Research Flow Diagram**

The research steps are required to be organized properly in order to simplify the composing of research report. The following Figure 3.4 is the presentation of the research steps.



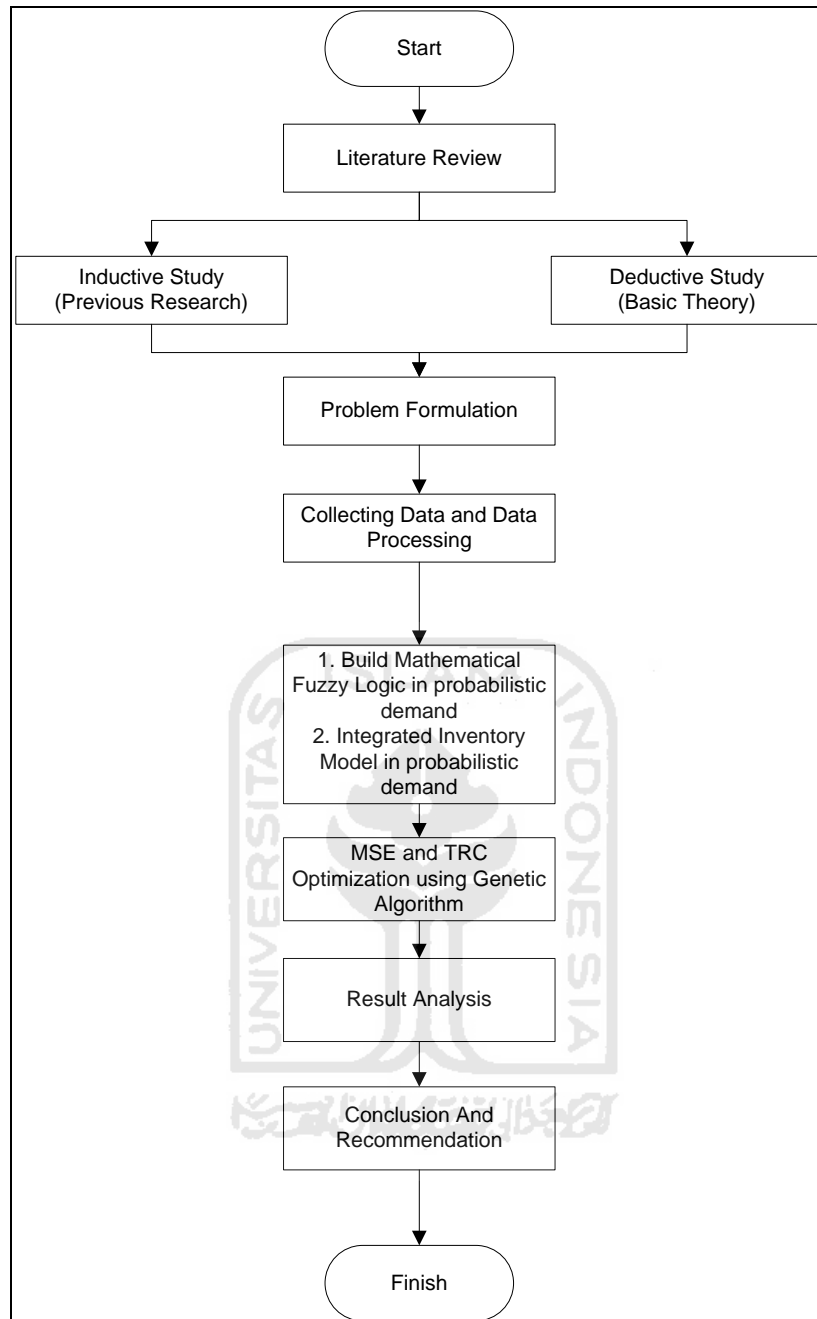


Figure 3.4 Research framework

## CHAPTER IV

### DATA COLLECTING AND DATA PROCESSING

#### 4.1 Data Collecting

This research uses secondary data obtained from previous researcher's data. The data is derived from two companies which are PT. Aseli Dagadu Djogdja (PT. ADD) as the purchaser and PT. Narigus as the vendor. PT. Narigus produces a paper hand bag to be used by PT. ADD to package the products. Detail data of both companies is explained in the following sub-chapter.

##### A. PT. ADD

Data about actual demand in year 2009, lead time, cost element, reorder point (ROP) of PT.ADD is shown in Table 4.1, Table 4.2, and Table 4.3 respectively.

Table 4.1 Actual Demand

Month	Demand
January	960
February	1026
March	1401
April	626
May	1827
June	905
July	527
August	1151
September	739
October	1861
November	1220
December	1745

Table 4.2 Lead Time Data

Lead time component (i)	Normal Duration (b <sub>i</sub> ) (days)	Minimum Duration (a <sub>i</sub> ) (days)	Unit crashing cost (c <sub>i</sub> ) (Rp/day)
1	4	2	10600
2	6	3	11000
3	2	1	8500
4	2	1	9000

Table 4.3 Element Cost Data

No	Cost Element	Detail elements	Quantity	Cost/unit
1	Purchase Order Cost (PO)	Making PO	125 minutes	-
		Printing PO	6 papers	Rp 500
		Sending PO	1 litre gasoline	Rp 4,500
2	Confirming PO	Short message service (Sms)	3 sms	Rp 350
		Phone	25 minutes	-
3	Purchase Cost/unit		1 pieces	Rp 550
4	Prime Holding Cost	warehouse electricity	1 month	Rp 200,000
		warehouse staff	1 month	Rp 400,000

Data about reorder point of PT ADD is 500 pieces.

#### B. PT. Narigus, Paper Bag Specialist

Data about actual inventory and production in year 2009, setup cost, production cost, primary holding cost, Percentage Decrease in  $\theta$  and Rupiah Increase in  $q(\theta)$ , back order and gross marginal data, and defective unit data of PT.Narigus is shown in Table 4.4, Table 4.5, Table 4.6, Table 4.7, Table 4.8, Table 4.9, and Table 4.10 respectively.

Table 4.4 Actual Inventory and Production

Month	Inventory (I)	Production (TP)
January	62	1022
February	238	1202
March	297	1460
April	262	591
May	280	1845
June	225	850
July	65	367
August	178	1264
September	235	796
October	216	1842
November	258	1262
December	315	1802

Table 4.5 Setup Cost

Detail Setup Cost	Quantity	Cost/unit	Total cost
Machine Preparing Time	10 minutes		
Working Time per month	9600 minutes		
Working Time per year	115200 minutes		
Regional Standard Salary	1	Rp. 480,000	Rp. 480,000

Table 4.6 Production Cost

Detail Production Cost elements	Cost/unit	Total cost
Paper	Rp. 175	Rp. 175
Plot	Rp. 100	Rp. 100
Rope	Rp. 125	Rp. 125
Paper Glue	Rp. 50	Rp. 50

Table 4.7 Primary Holding Cost

Detail elements	Quantity	Cost/unit	Total cost
Electricity	1 month	Rp. 400,000	Rp. 400,000
Warehouse staff	1 month	Rp. 480,000	Rp. 480,000
			Rp. 880,000

Table 4.8 Percentage Decrease in  $\theta$  and Rupiah Increase in  $q(\theta)$ 

Rupiah increase in $q(\theta)$	Percentage decrease in $(\theta)$
600	0.2

Table 4.9 Back Order and Gross Marginal Data

Back-order price discount/unit	Gross marginal profit /unit	Back order parameter
$\pi_x$	$\pi_0$	$\delta$
50	100	0.25

Table 4.10 Defective Unit Data

Percentage of defect	Defective unit	Production Cost/unit
0.002	50	450

### C. Integrated Data on Production Rate of PT. Dagadu and PT.Narigus

Data about production rate in year 2009 of PT ADD and PT.Narigus is shown as in

Table 4.11.

Table 4.11 Production Rate

Demand (D)	Inventory (I)	Production (TP)
960	62	1022
1026	238	1202
1401	297	1460
626	262	591
1827	280	1845
905	225	850
527	65	367
1151	178	1264
739	235	796
1861	216	1842
1220	258	1262
1745	315	1802

## 4.2 Data Processing



#### 4.2.1 Mathematical and Fuzzy Modeling

##### A. Determining the Input and Output Variables

The input variables to be analyzed are ( $D$ ) and ( $I$ ). The output variable is ( $TP$ ) which will be obtained through forecasting technique by considering the input variables.

##### B. Fuzzy Set and the Membership Function

Fuzzy set for ( $D$ ) and ( $I$ ) is shown in Figure 4.1 and Figure 4.2 respectively.

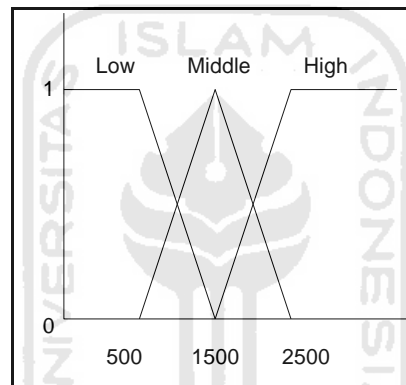


Figure 4.1 Fuzzy Set of ( $D$ )

$$\mu_{A \text{ low}}(x) = \begin{cases} 0; & x \geq 1500 \\ 1; & 0 \leq x \leq 500 \\ \frac{1500 - x}{1500 - 500} & 500 \leq x \leq 1500 \end{cases} \quad (4.1)$$

$$\mu_{A \text{ Middle}}(x) = \begin{cases} 0; & x \leq 500 \\ \frac{x - 500}{1500 - 500} & 500 \leq x \leq 1500 \\ \frac{2500 - x}{2500 - 1500} & 1500 \leq x \leq 2500 \\ 0; & x \geq 2500 \end{cases} \quad (4.2)$$

$$\mu_{A \text{ High}}(x) = \begin{cases} 0; & x \leq 1500 \\ 1; & x \geq 2500 \\ \frac{x - 1500}{2500 - 1500} & 1500 \leq x \leq 2500 \end{cases} \quad (4.3)$$

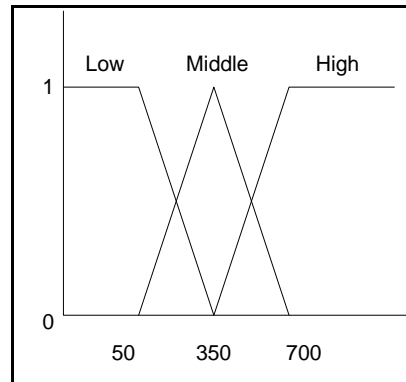


Figure 4.2 Fuzzy Set of (I)

$$\mu_{A \text{ low}}(x) = \begin{cases} 0; & x \geq 350 \\ 1; & 0 \leq x \leq 50 \\ \frac{350 - x}{350 - 50} & 50 \leq x \leq 350 \end{cases} \quad (4.4)$$

$$\mu_{A \text{ Middle}}(x) = \begin{cases} 0; & x \leq 50 \\ \frac{x - 50}{350 - 50} & 50 \leq x \leq 350 \\ \frac{700 - x}{700 - 350} & 350 \leq x \leq 700 \\ 0; & x \geq 700 \end{cases} \quad (4.5)$$

$$\mu_{A \text{ High}}(x) = \begin{cases} 0; & x \leq 350 \\ 1; & x \geq 700 \\ \frac{x - 350}{700 - 350} & 350 \leq x \leq 700 \end{cases} \quad (4.6)$$

### C. Fuzzy Rules

Fuzzy rules are determined based on full combination of the linguistic variables of each input data. Therefore, there will be 9 Fuzzy rules. Thus, the Fuzzy inference system to be used is Sugeno system and general form of the Fuzzy rules is shown in Equation 4.7.

$$R_i = \text{IF } D \text{ is } \tilde{D} \text{ AND } I \text{ is } \tilde{I} \text{ THEN } TP = a_i D + b_i I + c_i, \forall i, i = 1, \dots, 9$$

(4.7)

Where :  $\tilde{D}$  = Fuzzy universe of discourse of  $D$   
 $\tilde{I}$  = Fuzzy universe of discourse of  $I$   
 $a$  = weight of  $D$   
 $b$  = weight of  $I$   
 $c$  = constant  
 $i$  = rule index

Since there are 6 parameters in Fuzzy sets and 27 (9 x 3) parameters in Fuzzy rules, then the total number of parameters that can be adjusted (optimized) is 33. Firstly, these parameters value are randomly initialized. The initial value for the Fuzzy set is shown in Figure 4.1 and Figure 4.2 above while the initial value for the parameters in the Fuzzy rules is shown in Table 4.12.

Table 4.12 Rule Weight

<b>I</b>	<b>a</b>	<b>b</b>	<b>C</b>
1	1.5	0.2	0.3
2	0.7	1.1	0.5
3	0.1	0.6	0.7
4	0.2	0.3	0.8
5	1.3	0.0	1.2
6	0.7	1.7	0.9
7	0.2	1.3	1.0
8	0.5	0.6	0.4
9	0.6	1.5	0.9

#### **D. Summary of Fuzzy Calculation**

Summary of fuzzy calculation to forecast the production rate using initial value of each parameter is shown in Figure 4.3:

<i>Month</i>	<i>D</i>	<i>inv</i>	<i>TP</i>	<i>Rule</i>	<i>a cut</i>	<i>Demand</i>	<i>Inventory</i>	<i>Then Z</i>	<i>Forecast</i>	<i>Error<sup>2</sup></i>	
<i>Month</i> 1	960	62	1022	R1	0.5184	960	62	1403.6	727.61	1099.6	6027.1
				R2	0.4416	960	62	779.32	344.15		
				R3	0	960	62	138.78	0		
				R4	0.0216	960	62	215.97	4.665		
				R5	0.0184	960	62	1261.7	23.215		
				R6	0	960	62	738.7	0		
				R7	0	960	62	243.91	0		
				R8	0	960	62	510.24	0		
				R9	0	960	62	628.94	0		
<i>Month</i> 2	1026	238	1202	R1	0.177	1026	238	1530.6	270.85	1001.3	40262
				R2	0.1964	1026	238	1024.4	201.17		
				R3	0	1026	238	259.4	0		
				R4	0.297	1026	238	283.8	84.299		
				R5	0.3296	1026	238	1350.1	445.03		
				R6	0	1026	238	1083	0		
				R7	0	1026	238	479.06	0		
				R8	0	1026	238	642.27	0		
				R9	0	1026	238	936.3	0		
....											
....											
....											
<i>Month</i> 12	<i>D</i> 1745	<i>inv</i> 315	<i>TP</i> 1802	<i>Rule</i> R1	<i>a cut</i> 0	<i>Demand</i> 1745	<i>Inventory</i> 315	<i>Then Z</i> 2587		<i>Forecast</i> 2051.1	<i>Error<sup>2</sup></i> 62028
				R2	0.0881	1745	315	1641.9	144.62		
				R3	0.0286	1745	315	382.56	10.935		
				R4	0	1745	315	454.38	0		
				R5	0.6669	1745	315	2294.5	1530.2		
				R6	0.2164	1745	315	1687.8	365.27		
				R7	0	1745	315	699.83	0		
				R8	0	1745	315	1041.4	0		
				R9	0	1745	315	1453.7	0		

Figure 4.3 Summary of fuzzy calculation

The comparison between actual and prediction using initial value of each parameter is shown as in Figure 4.4.

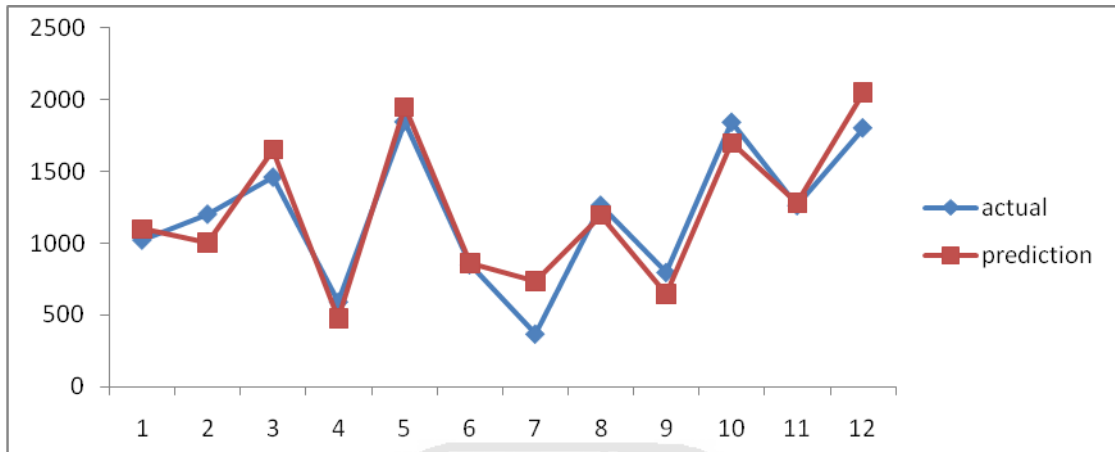


Figure 4.4 The comparison between actual and prediction of TP value

The summary of fuzzy calculation in Figure 4.3 shows that mean square error (MSE) of prediction is 29498 and the Percentage of Mean Error (PME) is 17.66%, it indicates a big error. This initial forecasting model shows that the model is still poor in accuracy, because the error is higher than 10 %, lead to invalidity of the model (Gelder, 1984). The small error prediction later will be the parameter in optimizing forecasting model. Genetic algorithm (GA) will be used for this purpose.

## 4.2.2 Integrated Inventory Model for Probabilistic

### 4.2.2.1 Data Integrated Inventory Model

Data input variables required for calculating integrated inventory model is as follow:

#### A. Demand in year

Number of demand data in year 2009 required for integrated inventory model is shown in Table 4.13.

Table 4.13 Number of demand

<b>Month</b>	<b>Demand</b>
January	960
February	1026
March	1401
April	626
May	1827
June	905
July	527
August	1151
September	739
October	1861
November	1220
December	1745
<b>Total Demand (D)</b>	<b>13988</b>

Average demand per month ( $\bar{D}$ ) =  $\frac{13988}{12} = 1165$  Unit

### **B. Standard Deviation of Expected Demand During Lead Time ( $\sigma$ )**

Standard deviation data required for calculating integrated inventory model is as follow:

#### **1. Expected demand During Lead time**

Data about expected demand during lead time is shown in Table 4.14.

Expected demand during lead time = Demand (pieces/days) \* Lead Time (days)

Table 4.14 Expected Demand during Lead Time

Demand	Lead Time (days)	Expected Demand During Lead Time
960	14	448
1026	14	478
1401	14	653
626	14	292
1827	14	852
905	14	422
527	14	245
1151	14	537
739	14	344
1861	14	868
1220	14	569
1745	14	814

Lead Time Demand<sub>1</sub> = 960 pieces/ 30 days \* 14 days = 448 pieces

Lead Time Demand<sub>2</sub> = 1026 pieces/ 30 days \* 14 days = 478 pieces

Lead Time Demand<sub>11</sub> = 1220 pieces/ 30 days \* 14 days = 569 pieces

Lead Time Demand<sub>12</sub> = 1745 pieces/ 30 days \* 14 days = 814 pieces

## 2. Mean of Expected Demand During Lead Time

Mean of expected demand during lead time ( $\bar{xL}$ ) can be determined is as follow:

$$\bar{xL} = \frac{448 + 478 + \dots + 814}{12} = 543$$

## 3. Standard Deviation of expected demand during lead time ( $\sigma\sqrt{L}$ ):

Standard Deviation of expected demand during lead time is as follow:

$$\sigma = \sqrt{\frac{\sum(x - \bar{xL})^2}{n - 1}}$$

$$= \sqrt{\frac{(448 - 543)^2 + (478 - 543)^2 + \dots + (814 - 543)^2}{12 - 1}}$$

$$\sigma = 214.59$$

### C. Safety Factor ( $k$ )

Safety factor data for calculating integrated inventory model is as follow:

Reorder Point ( $ROP$ ) = 500 pieces

$$ROP = \bar{x}L + k\sigma\sqrt{L}$$

$$k = \frac{ROP - \bar{x}L}{\sigma\sqrt{L}}$$

$$k = \frac{500 - 543}{214.59}$$

$$k = 0.2$$

### D. Purchaser's Ordering Cost per Order (A)

Data ordering cost required for calculating integrated inventory model is as follow:

1. Making PO : Rp. 7500

$$= \frac{150 \text{ minutes}}{\text{Working hour/year}} \times \text{Salary/year}$$

$$= \frac{150 \text{ minutes}}{115,200 \text{ minutes}} \times \text{Rp. 5,760,000}$$

2. Printing PO: 6 papers @ Rp. 500 : Rp. 3000

3. Sending PO: 1 liter @ Rp. 4500 : Rp. 4500

4. Confirming Order

By SMS: 3 sms @ Rp. 350 : Rp. 1050



By Phone: 25 minutes : Rp. 8500

Total of purchaser's ordering cost per order (A) : Rp. 24,550

#### E. Production rate ( $P$ )

Production data required for calculating integrated inventory model is the result of initial forecasting. Production data is shown in Table 4.15.

Table 4.15 Production Rate of initial Forecasting Result

Demand	Inventory	Production (Prediction)
960	140	1100
1026	116	1002
1401	368	1653
626	218	476
1827	342	1951
905	298	861
527	508	737
1151	553	1196
739	462	648
1861	300	1699
1220	364	1284
1745	671	2052
Total (P)		14659
Average		1221

Average Production/month ( $\bar{P}$ ):

$$\begin{aligned}
 &= \frac{\text{Total Production}}{12} \\
 &= \frac{14659}{12} = 1221 \text{ pieces/ month}
 \end{aligned}$$

#### F. Unit Production Cost Paid by the Vendor ( $C_v$ )

Unit production cost data is shown in Table 4.16.

Table 4.16 Unit Production Cost

Detail Production Cost elements	Cost/unit	Total cost
Paper	Rp. 175	Rp. 175
Plot	Rp. 100	Rp. 100
Rope	Rp. 125	Rp. 125
Paper Glue	Rp. 50	Rp. 50
Total		Rp. 450

### G. Unit Purchase Cost Paid by the Purchaser (*C<sub>p</sub>*)

Unit purchase cost data: Rp 550/pieces

### H. Annual Inventory Holding Cost per Rupiah Invested in Stock (*r*)

Annual inventory holding cost data per rupiah invested in stock is total value between holding cost rate for purchaser and vendor. It will be illustrated is as follow:

#### 1. Holding Cost Rate for Purchaser

Data about holding cost rate for purchaser is as follow:

##### a. Prime holding cost per month

Electricity : Rp. 200,000

Warehouse staff : Rp. 400,000 +  
Rp. 600,000

##### b. Average stock value (2009)

$$\begin{aligned}
 \text{Average stock value} &= \text{Average demand } (\bar{D}) * \text{Cost per item} \\
 &= 1165 \text{ pcs/mnth} * 12 \text{ mnth} * \text{Rp. } 550/\text{pcs} \\
 &= \text{Rp. } 7,689,000/\text{ year}
 \end{aligned}$$

##### c. Holding cost percentage per year

$$= \frac{\text{Primary holding cost}}{\text{Average stock value}} \times 100\%$$

$$= \frac{Rp. 7,200,000}{Rp. 7,689,000} \times 100\%$$

$$= 94\% = 0.94$$

## 2. Holding Cost Rate for Vendor

Data about holding cost rate for vendor is as follow:

a. Primary holding cost per month

Electricity : Rp. 400,000

Warehouse staff : Rp. 480,000 +

Rp. 880,000

b. Average stock value (2009)

Average stock value = Average production ( $\bar{P}$ ) \* Production cost/item

$$= 1221 \text{ pcs/ mnth} * 12 \text{ mnth} * Rp. 450/\text{pcs}$$

$$= Rp. 6,593,400/ \text{year}$$

c. Holding cost percentage per year

$$= \frac{\text{Primary holding cost}}{\text{Average stock value}} \times 100\%$$

$$= \frac{Rp. 10,560,000}{Rp. 6,593,400} \times 100\%$$

$$= 161\% = 1.61$$

## 3. Annual inventory holding cost per rupiah invested in stock ( $r$ )

Annual inventory holding cost per rupiah invested in stock is as follow:

$$r = \text{holding cost percentage purchaser} + \text{holding cost percentage vendor}$$

$$r = 2.54$$

### I. Vendor's Setup Cost per Setup (S)

Data about vendor's setup cost per setup is as follow:

$$\text{Setup cost} = \frac{\text{Machine preparation time}}{\text{Working hour}} \times \text{Regional standard salary}$$

$$\text{Setup cost} = \frac{10 \text{ minutes}}{115,200 \text{ minutes}} \times \text{Rp. } 5,760,000 \times 30\%$$

$$= \text{Rp. } 150$$

Optimal lot size ( $q^*$ ):

$$q^* = \sqrt{\frac{2 \cdot C_p \cdot r}{C_h}}$$

$$q^* = \sqrt{\frac{2 \times 150 \times 13988}{0.94 + 1.61}} = 1285$$

Number of Set-up:

$$\text{number of setup} = \frac{\text{Production rate}}{\text{Optimal lot size}}$$

$$\text{number of setup} = \frac{14659}{1285} = 12$$

Final Set-up Cost = set-up cost \* number of set-up

$$= \text{Rp. } 150 * 12$$

$$= \text{Rp. } 1800$$

### J. Out-of-control Probability

Out-of control probability data require for integrated inventory model is as follow:

Mean of production:  $\mu = \frac{\sum x}{n} = 1221$

Standard Deviation: 
$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{n-1}} = 518.12$$

Confidence Interval (99.98% confidence) is as follow:

$$(1-\alpha)100\% = 99.98\%$$

$$(1-\alpha) = \frac{99.98\%}{100\%}$$

$$(1-\alpha) = 0.9998$$

$$\alpha = 0.0002 / \theta_0 = 0.0002$$

$$\alpha = P \{ \text{Type 1 error} \}$$

$$= P \{ \text{Out of control signal is observed} \mid \text{Process is in control} \}$$

$$= P \{ \bar{X} < LCL \text{ or } \bar{X} > UCL \mid \text{True mean is } \mu \}$$

$$= P \{ \bar{X} < LCL \mid \mu \} + \{ \bar{X} > UCL \mid \mu \}$$

$$= P \left\{ \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < \frac{LCL - \mu}{\sigma/\sqrt{n}} \right\} + P \left\{ \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} > \frac{UCL - \mu}{\sigma/\sqrt{n}} \right\}$$

$$= P \left\{ Z < \frac{LCL - \mu}{\sigma/\sqrt{n}} \right\} + P \left\{ Z > \frac{UCL - \mu}{\sigma/\sqrt{n}} \right\}$$

Because the normal distribution is symmetric, then:

$$\frac{LCL - \mu}{\sigma/\sqrt{n}} = -z_{\alpha/2}, \quad \frac{UCL - \mu}{\sigma/\sqrt{n}} = z_{\alpha/2}$$

The  $z$  value, leaving an area of 0.0001 to the right and therefore an area of 0.9999 to the left, is  $z_{0.0001} = 3.49$  (Table of normal distribution), which gives:

$$UCL = \mu + \frac{\sigma z_{\alpha/2}}{\sqrt{n}}$$

$$UCL = 1221 + \frac{518.12 \times 3.49}{\sqrt{12}}$$

$$UCL = 1523$$

And

$$LCL = \mu - \frac{\sigma Z_{\alpha/2}}{\sqrt{n}}$$

$$LCL = 1221 - \frac{518.12 \times 3.49}{\sqrt{12}}$$

$$LCL = 920$$

### K. Percentage Decrease in $\theta$ per Rupiah Increase in $q(\theta)$

Percentage decrease data require for integrated inventory model is as follow:

$$\xi = \frac{\text{percentage decrease in } \theta}{\text{rupiah increase in } q(\theta)}$$

$$\xi = \frac{0.2}{600} = 0.0003333$$

### L. Quality Improvement

It is assumed that the quality improvement and capital investment,  $q(\theta)$  intended to reduce out-of-control probability by using logarithmic function of the out-of-control probability  $\theta$ . Quality improvement data is as follow:

$$q(\theta) = q \ln(\theta_0/\theta)$$

$$q = \frac{1}{\xi}$$

$$q = \frac{1}{0.00033333} = 3,000$$

### M. Fractional per Unit Time Opportunity Cost of Capital

Fractional per unit time data is as follow:

$$i = \frac{\pi_x}{\pi_0} \times \delta$$

$$i = \frac{50}{100} \times 0.25 = 0.125$$

**N. Cost of replacing a defective unit**

Data about Cost of replacing a defective is as follow:

$$g = \text{Percentage of Defect} \times \text{Defective Unit} \times \text{Production Cost}$$

$$g = 0.002 \times 50 \times 450 = \text{Rp. 45}$$

**4.2.2.2 Total Relevant Cost for Probabilistic Demand**

**A. Input variables for Total Relevant Cost:**

Summary calculation of input variables for initial integrated inventory model is shown in the Table 4.17.

Table 4.17 Parameter Input for TRC

Parameter	Value
$D$	13988
$P$	14659
$A$	24550
$S$	1800
$C_p$	550
$C_v$	450
$r$	2.54
$k$	0.200
$\sigma$	214.6
$i$	0.125
$g$	45
$Q$	3000
$\theta_0$	0.0002

The following procedure is constructed to find optimal values of  $Q$ ,  $m$ ,  $\theta$  and  $L$  for the problem under investigation. This model equation already explained in Chapter 3.

**Step 1.** For each  $L_i$ ,  $i = 1, 2, \dots, n$ , set  $\theta_i = \theta_0$  and perform (i)–(iii):

- (i) Substitute  $\theta_i$  into equation (3.20) to find  $m_i$ , and use  $\theta_i$  and  $m_i$  to compute  $Q_i$  using equation (3.15).

**Iteration 1**

Set  $\theta_i = \theta_0$ , so  $\theta_0 = 0.0002$ ,

$$R(L) = c_i[L_{i-1} - L] + \sum_{j=1}^{i-1} c_j(b_j - a_j)$$

$$R(L) = c_0[L_{0-1} - L] + \sum_{j=1}^{0-1} c_0(b_0 - a_0)$$

$$R(L) = 0$$

$$m^*(m^* - 1) \leq \frac{S(rC_p - (1 - 2D/P)rC_v)}{(A + R(L))(rC_v(1 - D/P) + gD\theta)} \leq m^*(m^* + 1)$$

$$m = \frac{S(rC_p - (1 - 2D/P)rC_v)}{(A + R(L))(rC_v(1 - D/P) + gD\theta)}$$

$$m_1 = \frac{1800(2.54 * 550 - (1 - 1.908)2.54 * 450)}{((24550 + 0)(2,54 * 450(0.0457)) + 45 * 13988 * 0.0002)}$$

$$m_1 = 1.0006$$

$$Q = \left[ \frac{2D(A + S/m + R(L))}{r(C_v(m(1 - D/P) - 1 + 2D/P) + C_p) + gmD\theta} \right]^{\frac{1}{2}}$$

$$= \left[ \frac{2 * 13988(24550 + 1800/1.0006 + 0)}{2,54(450(1.0006(0.0457) - 1 + 1.908) + 550) + 45 * 1.0006 * 13988 * 0.0002} \right]^{\frac{1}{2}}$$

$$Q_1 = 531$$

- (ii) Use  $Q_i$  and  $m_i$  to determine  $\theta_i$  from equation (3.16).

$$\theta = \frac{2iq}{gmDQ}$$



$$\theta_1 = \frac{2 * 0.125 * 3000}{45 * 1.0006 * 13988 * 531}$$

$$\theta_1 = 0.000002241207$$

(iii) Repeat (i) – (ii) until no change occurs in the values of  $Q_i$ ,  $m_i$  and  $\theta_i$ . Denote these solutions by  $Q_i^*$ ,  $m_i^*$  and  $\theta_i^*$ , respectively.

### Iteration 2

Set  $\theta_1 = 0.000002241207$ ;

$$m = \frac{S(rC_p - (1 - 2D/P)rC_v)}{(A + R(L))(rC_v(1 - D/P) + gD\theta)}$$

$$m_2 = \frac{1800(2.54 * 550 - (1 - 1.908)2.54 * 450)}{((24550 + 0)(2,54 * 450(0.0457)) + 45 * 13988 * 0.000002241207)}$$

$$m_2 = 1.8229$$

$$Q = \left[ \frac{2D(A + S/m + R(L))}{r(C_v(m(1 - D/P) - 1 + 2D/P) + C_p) + gmD\theta} \right]^{\frac{1}{2}}$$

$$= \left[ \frac{2 * 13988(24550 + 1800/1.8229 + 0)}{2,54(450(1.8229(0.0457) - 1 + 1.908) + 550) + 45 * 1.8229 * 13988 * 0.000002241207} \right]^{\frac{1}{2}}$$

$$Q_2 = 531$$

$$\theta = \frac{2iq}{gmDQ}$$

$$\theta_2 = \frac{2 * 0.125 * 3000}{45 * 1.8229 * 13988 * 531}$$

$$\theta_2 = 0.000001230291$$

### Iteration 3

Set  $\theta_2 = 0.000001230291$ ;

$$m = \frac{S(rC_p - (1 - 2D/P)rC_v)}{(A + R(L))(rC_v(1 - D/P) + gD\theta)}$$

$$m_3 = \frac{1800(2.54 * 550 - (1 - 1.908)2.54 * 450)}{((24550 + 0)(2,54 * 450(0.0457)) + 45 * 13988 * 0.000001230291)}$$

$$m_3 = 1.8338$$

$$Q = \left[ \frac{2D(A + S/m + R(L))}{r(C_v(m(1 - D/P) - 1 + 2D/P) + C_p) + gmD\theta} \right]^{\frac{1}{2}}$$

$$= \left[ \frac{2 * 13988(24550 + 1800/1.8338 + 0)}{2,54(450(1.8338(0.0457) - 1 + 1.908) + 550) + 45 * 1.8338 * 13988 * 0.000001230291} \right]^{\frac{1}{2}}$$

$$Q_3 = 531$$

$$\theta = \frac{2iq}{gmDQ}$$

$$\theta_3 = \frac{2 * 0.125 * 3000}{45 * 1.8338 * 13988 * 531}$$

$$\theta_3 = 0.000001222978$$

#### Iteration 4

Set  $\theta_3 = 0.000001222978$ ;

$$m = \frac{S(rC_p - (1 - 2D/P)rC_v)}{(A + R(L))(rC_v(1 - D/P) + gD\theta)}$$

$$m_4 = \frac{1800(2.54 * 550 - (1 - 1.908)2.54 * 450)}{((24550 + 0)(2,54 * 450(0.0457)) + 45 * 13988 * 0.000001222978)}$$

$$m_4 = 1.8339$$

$$Q = \left[ \frac{2D(A + S/m + R(L))}{r(C_V(m(1 - D/P) - 1 + 2D/P) + C_P) + gmD\theta} \right]^{\frac{1}{2}}$$

$$= \left[ \frac{2 * 13988(24550 + 1800/1.8339 + 0)}{2,54(450(1.8339(0.0457) - 1 + 1.908) + 550) + 45 * 1.8339 * 13988 * 0.000001222978} \right]^{\frac{1}{2}}$$

$$Q_4 = 531$$

$$\theta = \frac{2iq}{gmDQ}$$

$$\theta_4 = \frac{2 * 0.125 * 3000}{45 * 1.8339 * 13988 * 531}$$

$$\theta_4 = 0.000001222925$$

#### Iteration 5

Set  $\theta_4 = 0.000001222925$ ;

$$m = \frac{S(rC_P - (1 - 2D/P)rC_V)}{(A + R(L))(rC_V(1 - D/P) + gD\theta)}$$

$$m_5 = \frac{1800(2.54 * 550 - (1 - 1.908)2.54 * 450)}{((24550 + 0)(2,54 * 450(0.0457)) + 45 * 13988 * 0.000001222925)}$$

$$m_5 = 1.8339$$

$$Q = \left[ \frac{2D(A + S/m + R(L))}{r(C_V(m(1 - D/P) - 1 + 2D/P) + C_P) + gmD\theta} \right]^{\frac{1}{2}}$$

$$= \left[ \frac{2 * 13988(24550 + 1800/1.8339 + 0)}{2,54(450(1.8339(0.0457) - 1 + 1.908) + 550) + 45 * 1.8339 * 13988 * 0.000001222925} \right]^{\frac{1}{2}}$$

$$Q_5 = 531$$

$$\theta = \frac{2iq}{gmDQ}$$

$$\theta_5 = \frac{2 * 0.125 * 3000}{45 * 1.8339 * 13988 * 531}$$

$$\theta_5 = 0.000001222925$$

**Step 2.** If  $\theta_i^* \leq \theta_0$ , then the solution found in step 1 is optimal for the given  $L_i$ ;

Equation (3.11) will be used to compute  $TRC(Q_i^*, m_i^*, \theta_i^*, L_i)$ , for  $i = 0, 1, \dots$

,  $n$ , and go to step 4.

### Iteration 1

$$TRC_1(Q_1, m_1, \theta_1, L_1)$$

$$= \frac{D}{Q} \left[ A + \frac{s}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_V + rC_P + gmD\theta \right] + rC_P k \sigma \sqrt{L} + iq \ln \frac{\theta_0}{\theta}$$

$$= \frac{13988}{531} \left[ 24550 + \frac{1800}{1.006} + 0 \right]$$

$$+ \frac{531}{2} [(1.006(0.0457) - 1 + 1.908)1142 + 1395$$

$$+ 45 * 1.006 * 13988 * 0.000002241207]$$

$$+ 1395 * 0.2 * 214.6 * \sqrt{0.038} + 0.125 * 3000 \ln \frac{0.0002}{0.000002241207}$$

$$TRC_1(Q_1, m_1, \theta_1, L_1) = 1,367,866$$

### Iteration 2

$$TRC_2(Q_2, m_2, \theta_2, L_2)$$

$$= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{p} \right) - 1 + \frac{2D}{p} \right) rC_V + rC_P + gmD\theta \right] + rC_P k\sigma\sqrt{L} + iq \ln \frac{\theta_0}{\theta}$$

$$= \frac{13988}{531} \left[ 24550 + \frac{1800}{1.8229} + 0 \right]$$

$$+ \frac{531}{2} [(1.8229(0.0457) - 1 + 1.908)1142 + 1395$$

$$+ 45 * 1.8229 * 13988 * 0.000001230291]$$

$$+ 1395 * 0.2 * 214.6 * \sqrt{0.038} + 0.125 * 3000 \ln \frac{0.0002}{0.000001230291}$$

$$TRC_2(Q_2, m_2, \theta_2, L_2) = 1,358,147$$

### Iteration 3

$$TRC_3(Q_3, m_3, \theta_3, L_3)$$

$$= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{p} \right) - 1 + \frac{2D}{p} \right) rC_V + rC_P + gmD\theta \right] + rC_P k\sigma\sqrt{L} + iq \ln \frac{\theta_0}{\theta}$$

$$= \frac{13988}{531} \left[ 24550 + \frac{1800}{1.8338} + 0 \right]$$

$$+ \frac{531}{2} [(1.8338(0.0457) - 1 + 1.908)1142 + 1395$$

$$+ 45 * 1.8338 * 13988 * 0.000001222978]$$

$$+ 1395 * 0.2 * 214.6 * \sqrt{0.038} + 0.125 * 3000 \ln \frac{0.0002}{0.000001222978}$$

$$TRC_3(Q_3, m_3, \theta_3, L_3) = 1,358,146$$

### Iteration 4

$$TRC_4(Q_4, m_4, \theta_4, L_4)$$

$$\begin{aligned}
&= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_V + rC_P + gmD\theta \right] + \\
&rC_P k\sigma\sqrt{L} + iq \ln \frac{\theta_0}{\theta} \\
&= \frac{13988}{531} \left[ 24550 + \frac{1800}{1.8339} + 0 \right] \\
&+ \frac{531}{2} \left[ (1.8339(0.0457) - 1 + 1.908)1142 + 1395 \right. \\
&\left. + 45 * 1.8339 * 13988 * 0.000001222925 \right] \\
&+ 1395 * 0.2 * 214.6 * \sqrt{0.038} + 0.125 * 3000 \ln \frac{0.0002}{0.000001222925} \\
TRC_4(Q_4, m_4, \theta_4, L_4) &= 1,358,146
\end{aligned}$$

*Iteration 5*

$$\begin{aligned}
&TRC_5(Q_5, m_5, \theta_5, L_5) \\
&= \frac{D}{Q} \left[ A + \frac{S}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_V + rC_P + gmD\theta \right] + \\
&rC_P k\sigma\sqrt{L} + iq \ln \frac{\theta_0}{\theta} \\
&= \frac{13988}{531} \left[ 24550 + \frac{1800}{1.8339} + 0 \right] \\
&+ \frac{531}{2} \left[ (1.8339(0.0457) - 1 + 1.908)1142 + 1395 \right. \\
&\left. + 45 * 1.8339 * 13988 * 0.000001222925 \right] \\
&+ 1395 * 0.2 * 214.6 * \sqrt{0.038} + 0.125 * 3000 \ln \frac{0.0002}{0.000001222925} \\
TRC_5(Q_5, m_5, \theta_5, L_5) &= 1,358,146
\end{aligned}$$

Until this iteration, the value of  $m$ ,  $Q$ , and  $\theta$  are already constant, then continue to step ii to find the TRC. The values of TRC are depicted in the Figure 4.5.

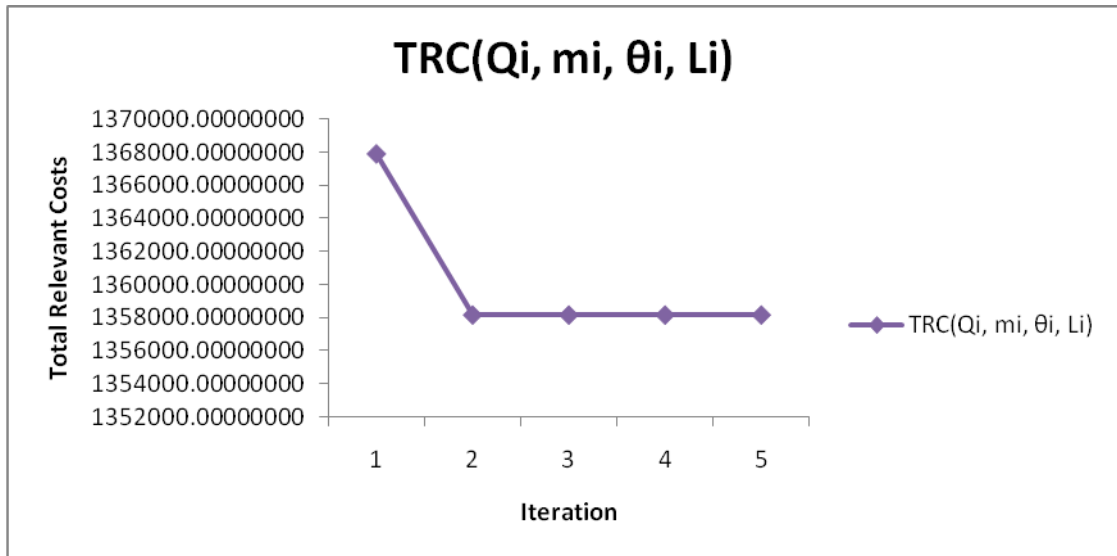


Figure 4.5 The value of TRC with variable  $m$ ,  $Q$ , and  $\theta$

**Step 3.** If  $\theta_i^* > \theta_0$ , set  $\theta_i^* = \theta_0$  for the given  $L_i$ , then substitute  $\theta_i^*$  into equation (3.20) to compute  $m_i^*$ , and use  $\theta_i^*$  and  $m_i^*$  to determine  $Q_i^*$  from equation (3.15); so use equation (3.11) to calculate  $TRC(Q_i^*, m_i^*, \theta_i^*, L_i)$ , for  $i = 0, 1, \dots, n$ .

**Step 4.** Set  $TRC(Q_s, m_s, \theta_s, L_s) = \min_{i=0,1,\dots,n} \{TRC(Q_i^*, m_i^*, \theta_i^*, L_i)\}$ . Then  $TRC(Q_s, m_s, \theta_s, L_s)$  is a set of optimal solutions.

Minimize  $TRC(Q^*, m^*, \theta^*, L^*)$

$$= \frac{D}{Q} \left[ A + \frac{s}{m} + R(L) \right] + \frac{Q}{2} \left[ \left( m \left( 1 - \frac{D}{P} \right) - 1 + \frac{2D}{P} \right) rC_V + rC_P + gmD\theta \right] + rC_P k \sigma \sqrt{L} + iq \ln \frac{\theta_0}{\theta}$$

$$= \frac{13988}{531} \left[ 24550 + \frac{1800}{1.8339} + 0 \right]$$

$$+ \frac{531}{2} \left[ (1.8339(0.0457) - 1 + 1.908)1142 + 1395 \right]$$

$$+ 45 * 1.8339 * 13988 * 0.000001222925]$$

$$+ 1395 * 0.2 * 214.6 * \sqrt{0.038} + 0.125 * 3000 \ln \frac{0.0002}{0.000001222925}$$

$$TRC_5(Q_5, m_5, \theta_5, L_5) = 1,358,146$$

This example TRC calculation only calculated using lead time  $i=0$ , then continue to calculate with  $i=1,2,3 \dots, n$  with same steps above. The summary of solutions procedure for  $m, Q, \theta, L$  and initial integrated inventory model is shown in Table 4.18 and Table 4.19

Table 4.18 Summaries of the solution procedure for  $m, Q, \theta, \text{ and } L$

$i$	$L_i$	$m_i$	$Q_i$	$\theta_i$	$TRC(Q_i, m_i, \theta_i, L_i)$
0	14	2	531	0.000001222925	1,358,147
1	12	2	725	0.000001222925	1,829,295
2	9	2	951	0.000001222925	2,378,438
3	8	1	1002	0.000001222925	2,499,657
4	7	1	1052	0.000001222925	2,621,698

Table 4.19 Summaries of Initial Integrated inventory model

	<b>Initial integrated inventory model</b>
<b>Purchaser order lot size (<math>Q</math>)</b>	531
<b>Vendor produce lot size (<math>Q</math>)</b>	1062
<b>Lead time (<math>L</math>)</b>	14.00
<b>Number of Deliveries (<math>m</math>)</b>	2.00
<b>Probability of process being out of control (<math>\theta</math>)</b>	0.000001223
<b>Joint total annual cost</b>	Rp 1,358,147
<b>MSE</b>	29498.19
<b>PME</b>	17.66

The results of total relevant cost (TRC) using Integrated Inventory model is already determined, but it still considered as invalid because the input value from initial forecasting, still have big error which is more than 10%. Thus, optimization technique is required to optimize integrated inventory model. GA will be used for this purpose.

### 4.2.3 Objective Function/Fitness Function

Since the forecasting model gives inaccurate solution, it will affect to the result of total relevant cost. In order to find optimal integrated inventory model, minimizing the



error of forecasting and total relevant cost is become the major objective function for this research. The Objective function can be formulated is as follow:

Objective Function is is as follow:

$$W1=0.013$$

$$W2=0.014$$

Where,

A is MSE variable,

B is TRC variable,

W is parameters value of randomly initialized

$$\text{Objective Function} = \frac{AxW1 + BxW2}{W1 + W2}$$

### 4.3 GA Optimization

GA is implemented to this research to optimize the integrated inventory model that already explained in Chapter three. The stage of solving problem is as follow.

#### 4.3.1 Initialization

The important thing to solve the problem by using GA is the representation of chromosome. Chromosome is collection of gen that collaborates to establish the string value. The chromosome is shown in Figure 4.6.

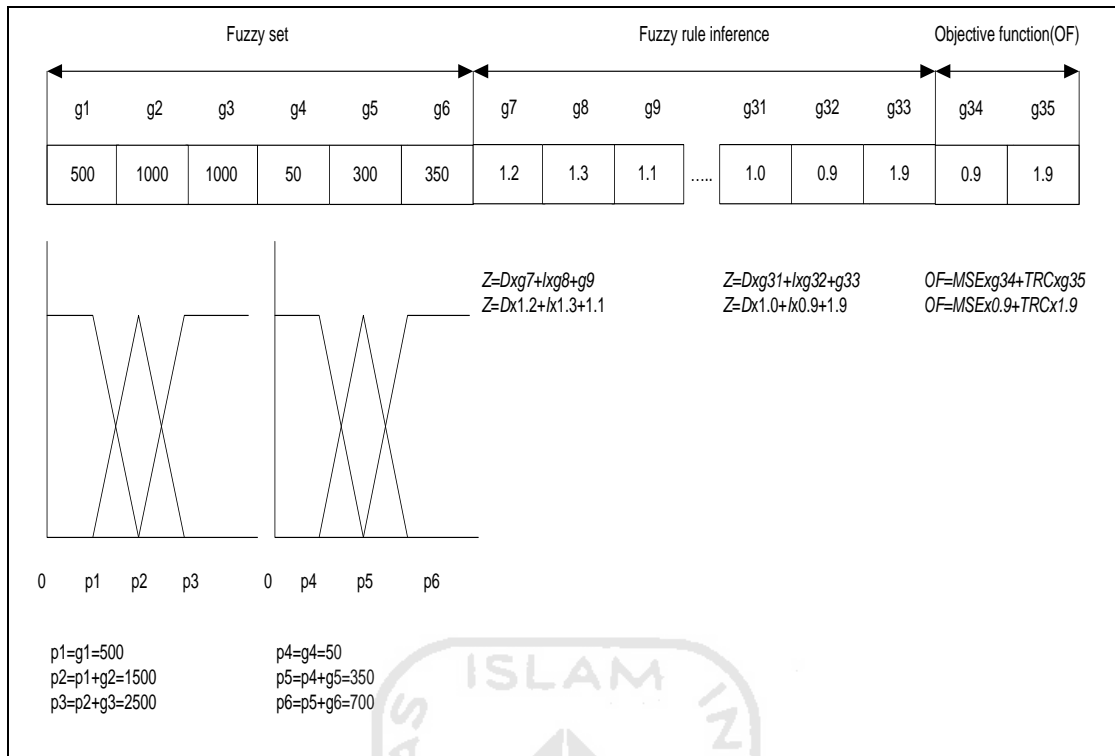


Figure 4.6 The representation of chromosomes

### 4.3.2 Selection

Selection is used to choose the best individual chromosome of population. Selection is conducted to avoid premature convergence. The Higher fitness value of individual chromosome, more likely it will be selected. This research is uses roulette wheel that already explain in Chapter three. The selection procedure is shown in Figure 4.7.

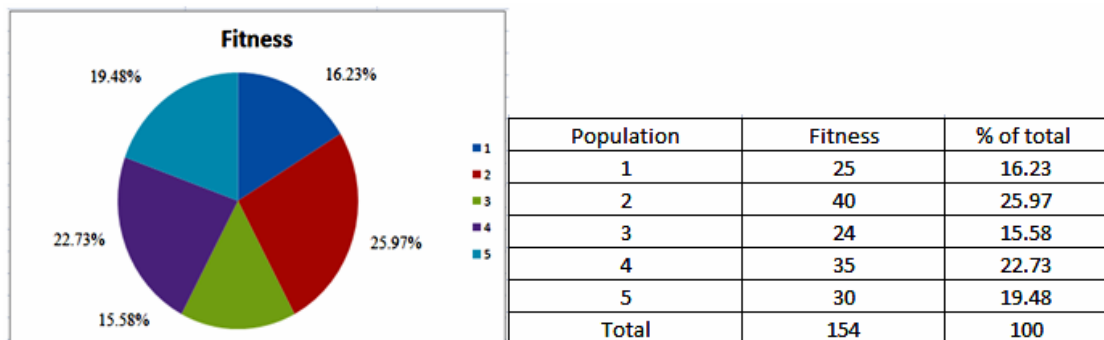


Figure 4.7 Representation of selection

### 4.3.3 Crossover

Crossover is operator of GA which involving two parents to produce new chromosomes. Two parents are chosen by randomly from the populations that already determined. To produce new chromosomes, crossover is conducted randomly by choosing two meeting points from gen string. The gen between two cut points will be replaced among a couple populations that already determined. The representation of crossover is shown in Figure 4.8.

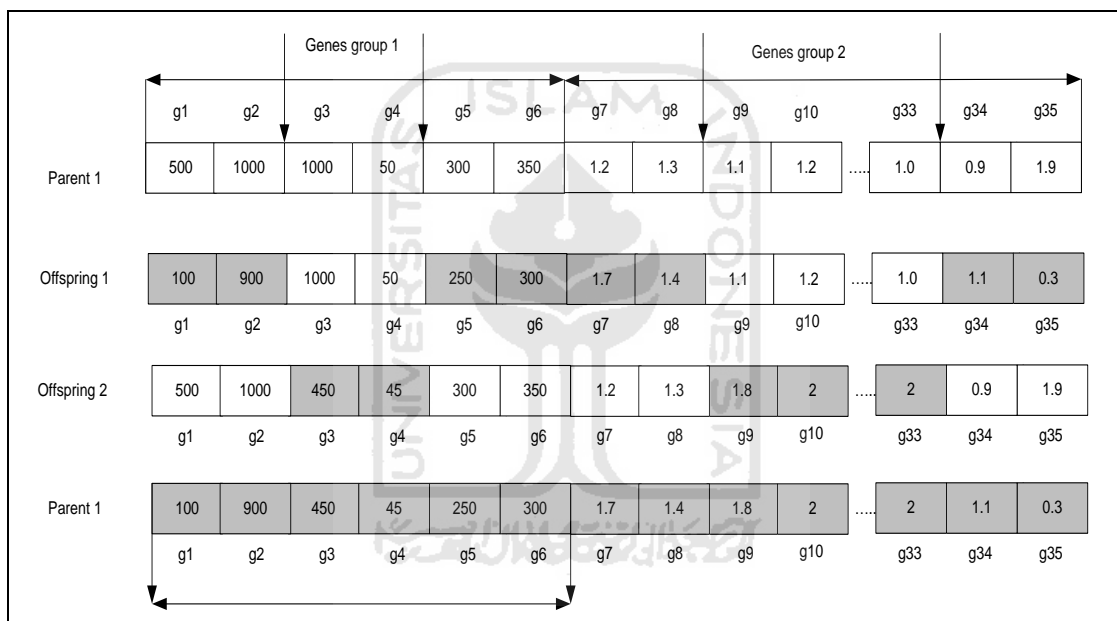


Figure 4.8 Representation of two cut points crossover

### 4.3.4 Mutation

After crossover process is occurred, then followed by mutation process. Mutation is purposed to improve the performance settlement in crossover which involving replacement of two gen elements that chosen by randomly. The mutation process is shown in Figure 4.9.

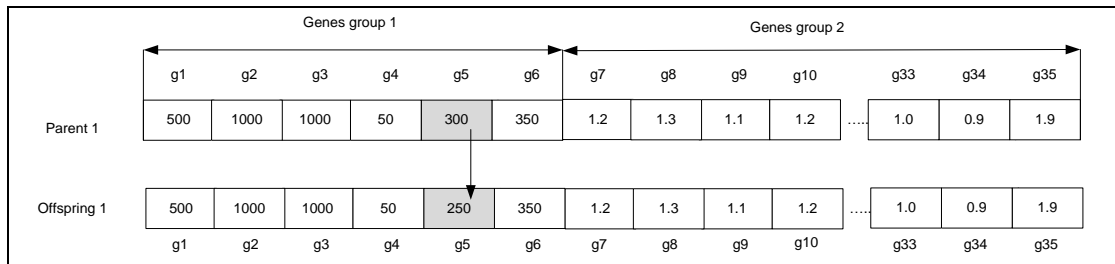


Figure 4.9 Representation of mutation

#### 4.3.5 Problem Definition in GA Generator

The problem that already formulated in Microsoft<sup>®</sup> Excel, then connected to the generator GA NLI-gen<sup>®</sup>. Previously, all problem parameters are must be defined. The purpose is to connect those parameters with GA operator. The Catalog dialog to enter the parameters in generator GA NLI-gen<sup>®</sup> is shown in Figure 4.10.

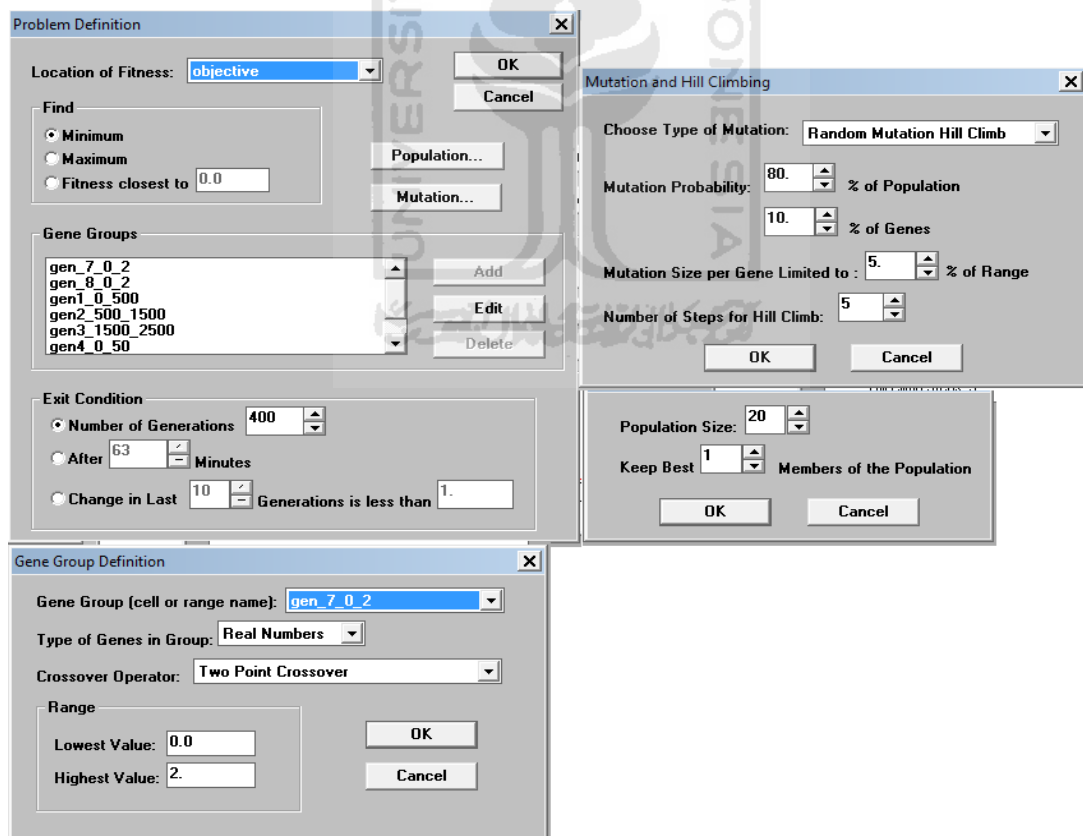


Figure 4.10 Problem Definitions in Generator

The steps to run generator GA NLI-gen<sup>®</sup> is as follow:

1. Chose the Fitness Location
2. Chose the objective function is maximum or minimum
3. Set mutation and hill climbing.
  - a. Set mutation probability is 80% of population. It means that 80% of population will perform mutation in each generation.
  - b. Set mutation probability is 10% of gen. It means that 10% of gen will perform mutation in each generation.
  - c. Set mutation size per gene limited to 5% of range. It means that the gen may conduct mutation until 5% of range of gen that already determined.
  - d. Set type of mutation is the random mutation hill climbing. It means that random mutation is conducted by continuously, and only the best result will be more likely to be chosen.
5. Set Population
  - a. Population size is 20. It means that there are 20 chromosomes will be paired.
  - b. Keep best is 1
6. Determine the gene group, type of gen, crossover operator and the range of gen.
  - a. Type of gen as real number
  - b. Set type of crossover is 2 point cross over.
  - c. Determine the range real number for each gen

### 4.3.6 Termination

Based on experiments, the termination result is appeared to be near/ optimum, which is 400 generations. The searching process of GA and GA status optimization is shown in Figure 4.11 and Figure 4.12 respectively.

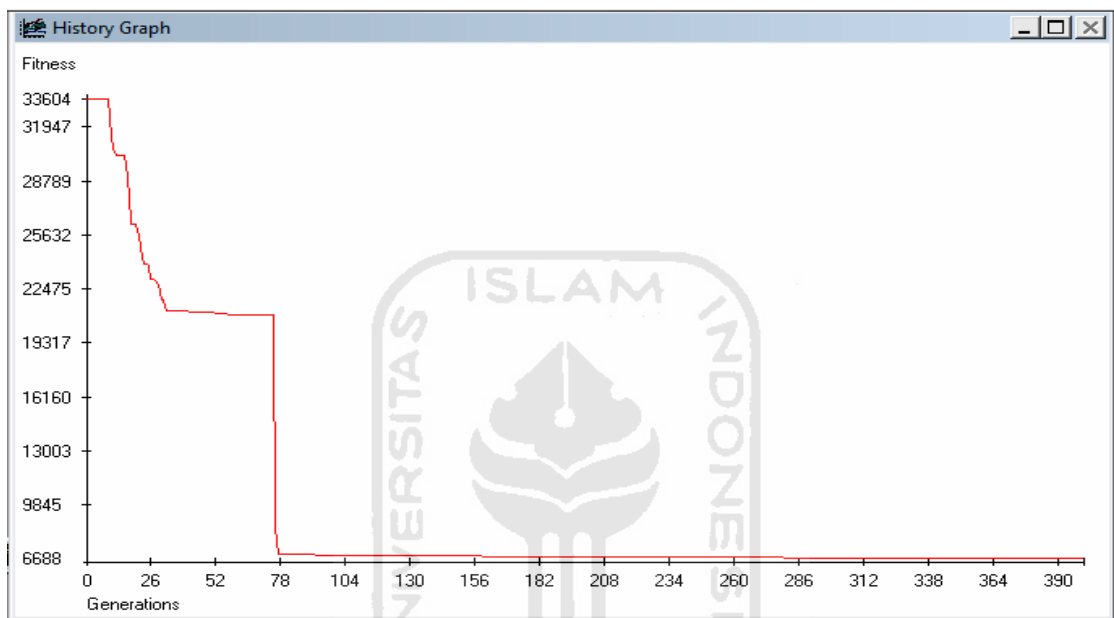


Figure 4.11 Searching process of GA

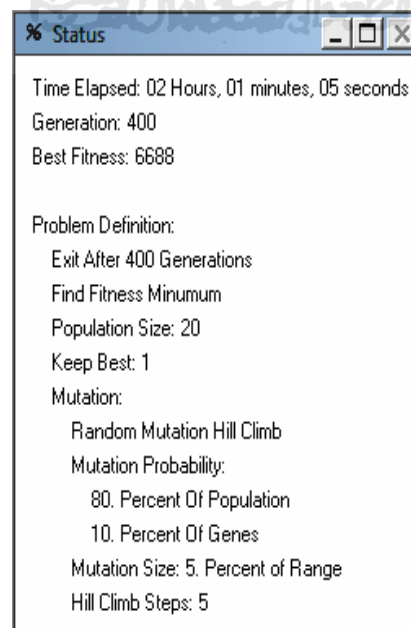


Figure 4.12 Status of Genetic Algorithm

### 4.3.7 Genetic Algorithm Optimization Result

The result of optimization using genetic algorithm by comparing among populations will be described is as follow:

Table 4.20 Comparison result of genetic algorithm optimization

	<b>Pop 20</b>	<b>Pop 30</b>	<b>Pop 40</b>	<b>Pop 50</b>
<b>Purchaser order lot size (<math>Q</math>)</b>	<b>522</b>	523	522	522
<b>Vendor produce lot size (<math>Q</math>)</b>	<b>1566</b>	1569	1566	1566
<b>Lead time (<math>L</math>)</b>	<b>14</b>	14	14	14
<b>Number of Deliveries (<math>m</math>)</b>	<b>3</b>	3	3	3
<b>Probability of process being out of control (<math>\theta</math>)</b>	<b>0.000000905</b>	0.000000867	0.000000872	0.000000875
<b>Joint total annual cost</b>	<b>Rp1,366,703</b>	Rp1,367,435	Rp1,367,487	Rp1,367,158
<b>MSE</b>	<b>2572</b>	1629	2361	1627
<b>PME</b>	<b>4.33</b>	2.75	3.32	2.32
<b>Objective Function</b>	<b>6688</b>	1578	2444	2054

The best result is obtained on 20 size of population that have MSE is 2572 and PME is 4.33%. Total relevant cost of integrated inventory is Rp. 1,366,703.

### 4.4 Fuzzy Model after Optimization

The summary of fuzzy calculation to forecast total production after optimization has MSE is reduced from 29,498.18 to 2572 and PME reduced from 17.66% to 4.33 %. Below, the figure of summary of fuzzy calculation and figure of actual and prediction after optimization with twenty size of population is shown in Figure 4.13 and Figure 4.14 respectively.

<i>Month</i>	<i>D</i>	<i>inv</i>	<i>TP</i>	<i>Rule</i>	<i>a cut</i>	<i>Demand</i>	<i>Inventory</i>	<i>Then Z</i>	<i>Forecast</i>	<i>Error<sup>2</sup></i>			
<i>Month</i> 1	960	62	1022	R1	0.3614	960	62	651.64	235.49	991.4	936.14		
				R2	0.59	960	62	1204	710.41				
				R3	0	960	62	583.79	0				
				R4	0.0185	960	62	953.05	17.591				
				R5	0.0301	960	62	926.28	27.914				
				R6	0	960	62	874.87	0				
				R7	0	960	62	848.95	0				
				R8	0	960	62	995.41	0				
				R9	0	960	62	1524.1	0				
<i>Month</i> 2	1026	238	1202	<i>Rule</i>		<i>Demand</i>		<i>Then Z</i>		<i>Forecast</i>		<i>Error<sup>2</sup></i>	
				R1	0.0933	1026	238	697.4	65.04	1088.7	12841		
				R2	0.2207	1026	238	1465.6	323.39				
				R3	0	1026	238	793.89	0				
				R4	0.2038	1026	238	1049.4	213.91				
				R5	0.4823	1026	238	1008.5	486.35				
				R6	0	1026	238	1220.9	0				
				R7	0	1026	238	1193.1	0				
				R8	0	1026	238	1304.8	0				
				R9	0	1026	238	1805.3	0				
<i>Month</i> 12	1745	315	1802	<i>Rule</i>		<i>Demand</i>		<i>Then Z</i>		<i>Forecast</i>		<i>Error<sup>2</sup></i>	
				R1	0	1745	315	1185.6	0	1797.4	20.983		
				R2	0.0213	1745	315	2397.9	51.065				
				R3	0.0137	1745	315	1261	17.288				
				R4	0	1745	315	1768.5	0				
				R5	0.5871	1745	315	1705.2	1001.1				
				R6	0.3779	1745	315	1926.3	728				
				R7	0	1745	315	1879	0				
				R8	0	1745	315	2092.3	0				
				R9	0	1745	315	2977.5	0				

Figure 4.13. Summary of fuzzy calculation after optimization



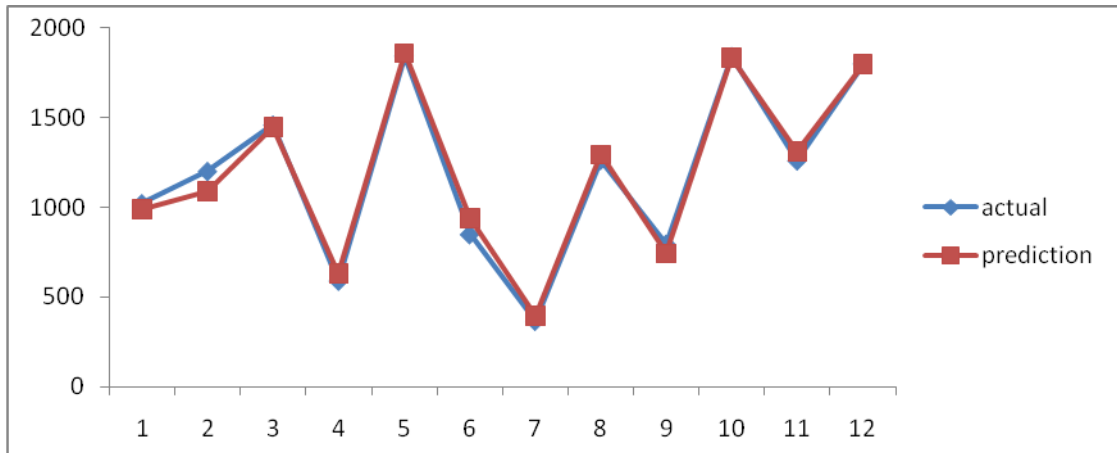


Figure 4.14 Actual and prediction graph after optimization

#### 4.5 Total Relevant Cost after Optimization

The summary of parameter inputs that will be processed using integrated inventory model after optimization is shown in Table 4.21.

Table 4.21 Parameter Input after optimization

Parameter	Value
$D$	13988
$P$	14341
$A$	24550
$S$	1800
$C_p$	550
$C_v$	450
$r$	2.57
$k$	0.200
$\sigma$	214.61
$i$	0.125
$g$	45
$q$	3000
$\theta_0$	0.0002

It will be further calculated with the same formula that already shown above. The following procedure is constructed to find optimal values of  $Q$ ,  $m$ ,  $\theta$  and  $L$  for the problem under investigation. This model already explained in Chapter 3. The values of TRC are depicted in the Figure 4.15 below:

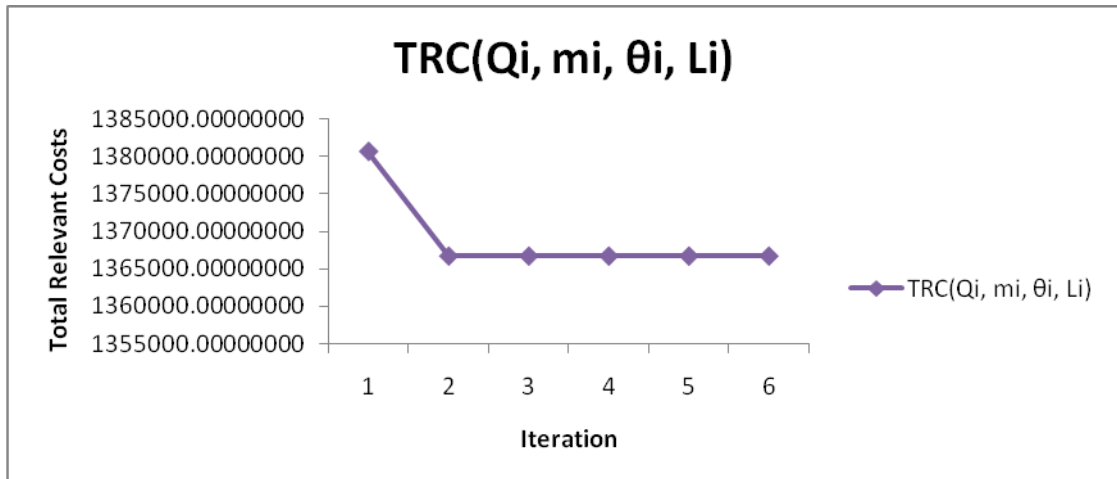


Figure 4.15 The value of TRC with variable  $m$ ,  $Q$ , and  $\theta$

The summaries solution of optimal  $m$ ,  $Q$ ,  $\theta$ , and  $L$  is shown in Table 4.22.

Table 4.22 Summaries solution of optimal  $m$ ,  $Q$ ,  $\theta$ , and  $L$  after optimization

$i$	$L_i$	$m_i$	$Q_i$	$\theta_i$	$TRC(Q_i, m_i, \theta_i, L_i)$
0	14	3.00000	522	0.000000905261948520	1366703
1	12	2.00000	713	0.000000905261948355	1845765
2	9	2.00000000	936	0.000000905261948408	2404133
3	8	2.00000000	985	0.000000905261948414	2527389
4	7	2.00000000	1035	0.000000905261948414	2651481

#### 4.6 Result Summary

The result summary by following steps above shows that initial forecasting have MSE 29,498.18, PME is 17.66, and the total relevant cost is Rp. 1,358,147. It can be conclude that the solution is still in poor accuracy because the error of forecast is more than 10%. Minimizing the error and total relevant cost is parameters of optimal integrated inventory. Then GA is used for this purpose. After optimization, MSE reduce from 29,498.18 to 2572, PME reduce from 17.66% to 4.33%, and total relevant cost is Rp. 1,366,703. It can be concluded fairly that the solution is valid.

## CHAPTER V

### DISCUSSION

It is generally known that the demand is often related with fluctuating condition. It will affect directly to the production planning and inventory control. In line with the problem formulation in Chapter I, this research is concerned to optimize integrated inventory model in Just in Time (JIT) purchasing by involving the fuzzy logic model to forecast the production number to deal with uncertainty demand. The objective of integrated inventory model is to minimize the total relevant cost that consist of the sum of ordering cost, holding cost, quality improvement investment, and crashing cost. Therefore, the parameters are being set to optimize integrated inventory model by minimizing the prediction error and the total relevant cost.

Based on the result from the previous chapter, the first step is building causal forecasting model using fuzzy logic. There are several things that can be discussed related to the fuzzy logic model. The first is about the number of fuzzy rules used in fuzzy logic model. The number of fuzzy rules used in this study has 9 rules where each rules have an effect on the output or not. Fuzzy rules are determined based on full combination of the linguistic variables of each input data. Each fuzzy rule has a value called the membership value. The membership value has ranges between 0 until 1. If the value of membership value is zero, it means that the rule does not have any effect to the output. There are 12 data that already tested for each rule. For rule number 1 gives the effect on output by 75%, rule number 2 is 100%, rule number 3 is 25%, rule number 4 is 75%, rule number 5 is 100%, and rule number 6 is 25%. Nevertheless, for rule 7, 8, and 9 had no effect at all to the output. Therefore, it can be

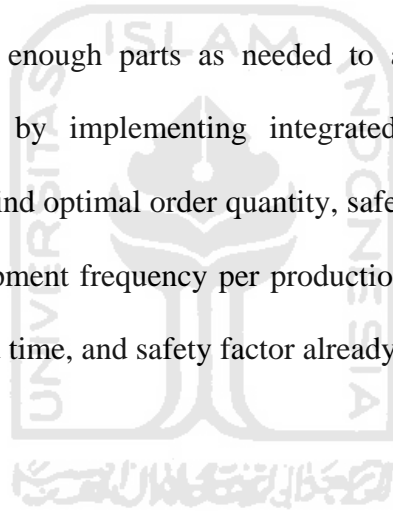
concluded that rule 1, 2, 3, 4, 5, and 6 give effect to the output, while rule 7, 8, and 9 can be eliminated because those rule had no effect at all to the output. The second, initial forecasting result shows that mean square error (MSE) is 29,498 and percentage mean of error (PME) is 17.66% that indicated more than 10%. Before optimizing initial forecasting model is conducted, it is required to calculate total relevant cost using integrated inventory model for buyer and vendor. Applying the solution procedure of integrated inventory model, it can be seen that the optimal lead time is  $L_s = 14$  days, optimal number of deliveries  $m_s = 2$ , optimal probability  $\theta_s = 0.000001223$ , optimal order quantity  $Q^* = 531$  units and total relevant cost is Rp 1,385,147.

Since the result of forecasting has a big error. Consequently, the model is still poor in accuracy and the result of forecasting will affect directly to the validity of integrated inventory solution. As explained above, minimizing the error of prediction and minimum total relevant cost will optimize the integrated inventory model. The (GA) is used to this purpose. In order to justify the optimality of the solution provided by GA, two parameters will be used, that are: the premature convergent is not occurred in the searching process and the chromosomes can be improved in every generation therefore the hill climbing phenomenon is occurred. The optimization conducted by comparing among populations, that are 20, 30, 40, and 50 populations. In comparison among populations provides different results. It is caused by the size of population. If the size of population is higher so it is likely there will be duplication of chromosome that causes differences in the searching process to achieve the optimal solution.

From resulting solution shows that population 20 has the best result than other populations. The error prediction is reduce from 29,489 to 2572 and percentage mean error is 4.33% with total relevant cost Rp. 1,366,703 which smaller than other

populations. From the results it is concluded that the prediction error is reduced 91.2% after optimized. The small prediction errors show that the forecasting model is more valid than before. Applying the solution procedure of integrated inventory model, it can be seen that the optimal lead time is  $L_s = 14$  days, optimal number of deliveries  $m_s = 3$ , optimal probability  $\theta_s = 0.000000905$ , and optimal order quantity  $Q^* = 522$  units.

From the result above, by involving fuzzy logic model in integrated inventory model provides advantage to determine total production for uncertainty demands. Optimal integrated inventory model is refer to JIT purchasing which is to establish a long term relationship with the vendor to maintain regulated shipments to minimize ordering cost and to buy enough parts as needed to avoid paying holding cost. Moreover, the advantage by implementing integrated inventory model in JIT purchasing for buyer is to find optimal order quantity, safety factor, and lead time. For vendor to find optimal shipment frequency per production cycle (integer) and taking optimal order quantity, lead time, and safety factor already determined for the buyer.



## CHAPTER VI

### CONCLUSION AND RECOMMENDATION

#### 6.1 Conclusion

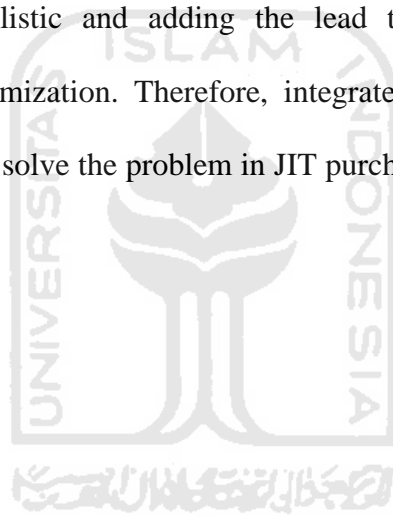
According to the explanation in chapter V, some conclusions can be established as follows:

1. The model based on optimized fuzzy logic has the error less than ten percent in order for the result of prediction to be closer to actual conditions. The result of forecasting using a fuzzy logic model has a prediction error of 29,498 and a percentage error of 17.66%. After it is optimized using a genetic algorithm, the result has a prediction error of 2572 and a mean error percentage of 4.33%. It is indicated that the smaller the prediction error, the more valid the model will be.
2. Total relevant cost is optimized using a genetic algorithm (GA) by comparing among populations. The result shows that a population size of 20 in GA has the best result of total relevant cost, which is Rp. 1,366,703, smaller than other populations. Applying the solution procedure of an integrated inventory model, it can be shown that the optimal lead time is  $L_s = 14$  days, optimal number of deliveries  $m_s = 3$ , optimal probability  $\theta_s = 0.000000905$ , and optimal order quantity  $Q^* = 522$  units.

## 6.2 Recommendation

Some recommendations after conducting this research described as follow:

1. By involving the optimized fuzzy logic in integrated inventory model when demand is probabilistic, the company can implement this model to reduce the cost related with production planning and enhance the relationships between buyer and vendor.
2. As the developments of research and technology, further research can involve artificial neural network in integrated inventory for buyer and vendor when demand is probabilistic and adding the lead time and crashing cost as parameters for optimization. Therefore, integrated inventory model will be more appropriate to solve the problem in JIT purchasing and dynamic business environment.



## REFERENCE

- Askin, Ronald G., and Standridge, Charles R., (1993). *Modeling and Analysis of Manufacturing System*. John Wiley & Sons, New York.
- Chang, H.C., (2004). An application of fuzzy sets theory to the EOQ model with imperfect quality items. *Compute. Operation. Res.*, 31: 2079-2092.
- Chen, S.H. and C.C. Wang, (1996). Backorder fuzzy inventory model under functional principle. *Inform. Sci.*, 95: 71-79.
- Gelders, L., (1984). *Quantitative Methods in Management: An Introduction to Waiting-Lines, Inventory Models, and Replacement Theory*. Katholieke Universiteit Te Leuven. Leuven-Heverlee.
- Gen, M dan Cheng, R., (1997). *Genetic Algorithms And Engineering Design*. USA: John Wiley & Sons, Inc
- Gen Mitsuo and Cheng Runwei, (2000). *Genetic Algorithm and Engineering Optimization*, John Wiley & Son, Inc, New York.
- Goldberg, D. E., (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. USA: Addison-Wesley Publishing Company, Inc
- Goyal, S.K., (1988). A joint economic lot size model for purchaser and vendor: A comment. *Decision Sci.*, 19: 236-241.
- Goyal, S.K. and Gupta, Y. P.,(1989). Integrated Inventory models; the buyer-vendor coordination. *European Journal of Production Research*, 41, 261-269.



- Gunasekaran, A., (1999). Just-in-time purchasing: an investigation for research and applications. *International Journal of Production Economics*, 59, 77–84.
- Ha, D. and S.L. Kim, (1997). Implementation of JIT purchasing: An integrated approach. *Prod. Plan. Control*, 8: 152-157.
- Hanke, J. E., Reitsch, A. G. & Wichern, D. (1998). *Business Forecasting (6th ed.)*, Englewood Cliffs, NJ: Prentice-Hall.
- Ho, C., (1989). Evaluating the impact of operating environments on MRP system nervousness. *International Journal of Production Research* 27, 1115–1135.
- Huang, C.K., (2002). An integrated vendor-buyer cooperative inventory model for items with imperfect quality. *Prod. Plann. Control*, 13: 355-361.
- Klir, G. and Yuan, B. (1995). *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Prentice Hall, Inc. New Jersey.
- Krajewski, J. and Ritzman, B., (1996). *Operation Management Strategy and Analysis. Fourth Edition*. Addison-Wesley Publishing Company.Inc
- Lee, C.Y, Piramuthu, S and Tsai, K.Y, (1997). Job shop scheduling with a Genetic Algorithm and Machine learning. *International Journal Production Research*, 35 no.4, 1171-1191.
- Lee, H.M. and J.S. Yao, (1998). Economic production quantity for fuzzy demand quantity and fuzzy production quantity. *Eur. J. Oper. Res.*, 109: 203-211.
- Markland, Robert E., and Sweigart, James R., (1987). *Quantitative Methods: Applications to Managerial Decision Making*. John Wiley & Sons, New York.

- Martinich, J. C., (1997). *Production and Operations Management*. John Wiley & Sons, New York.
- Monden, Y., (1995). *Cost Reduction System: Target Costing and Kaizen Costing*. Portland, Oregon, Productivity Press.
- Monika., (2010). Optimasi Demand dan Lead Time Delivery Probabilistik Model Integrasi Inventory Industri dan Pemasok. Thesis, Universitas Islam Indonesia, Yogyakarta, (Unpublished)
- Mun, J. (2006). *Modeling Risk: Applying Monte Carlo Simulation, Real Options Analysis, Forecasting and Optimization Technique*. John Willey & Sons, Inc. New Jersey.
- Nahmias, S. (2001). *Production and Operation Analysis. Fourth Edition*. McGraw-Hill Companies, Inc. Singapore.
- Pan, J. C. H., and Yang, J. S., (2002). A study of an integrated inventory with controllable leadtime. *International Journal of Production Research*, 40, 1263–1273.
- Pan, J. C. H., and Yang, J. S., (2004). Just-in-time purchasing: an integrated inventory model involving deterministic variable lead time and quality improvement investment. *International Journal of Production Research*, 42/5, 853-863.
- Pham, D.T., & Karaboga. D., (2000). *Intellegent Optimisation Techniques*. Springer Verlag, London Limited

- Porteus, E. L., (1986). Optimal lot sizing, process quality improvement and setup cost reduction. *Operations Research*, 34, 137–144.
- Ross, T.J. (2004). *Fuzzy Logic with Engineering Applications*. Second Edition. John Willey & Sons, Inc. England.
- Roy, T.K. and M. Maiti, (1997). A fuzzy EOQ model with demand-dependent unit cost under limited storage capacity. *Eur. J. Oper. Res.*, 99: 425-432.
- Schonberger, R. J., and Ansari, A., (1984). Just-in-time purchasing can improve quality. *Journal of Purchasing and Materials Management*, 20, 2–7.
- Sri Kusumadewi, and Hari Purnomo, (2004). *Aplikasi Logika Fuzzy Untuk Pendukung Keputusan*. Yogyakarta: Graha Ilmu.
- Stefan, W., S. Stefan, V.B. Christophe and H.F. Philip, (2004). Vertical marketing systems for complex products: A triadic perspective. *J. Market. Res.*, 41: 479-487.
- Tersine, R. J., (1994). *Principles of Inventory and Materials Management*. Fourth Edition. Prentice-Hall, Inc. New Jersey.
- Thomas, D. J., and Griffin, P. M., (1996). Coordinated supply chain management. *European Journal of Operational Research*, 94, 1-15.
- W.E. Combs and J.E. Andrews (1998). Combinatorial rule explosion eliminated by a fuzzy rule configuration, *IEEE Trans. Fuzzy Syst.*, 6, pp. 1-11.

Yao, J.S., S.C. Chang and J.S. Su, (2000). Fuzzy inventory without backorder for fuzzy order quantity and fuzzy total demand quantity. *Comput. Operat. Res.*, 27: 935-962.

Zenz, Gary J., (1994). *Purchasing and The Management of Materials*. Seventh Edition. John Wiley & Sons, New York.



## APPENDICES

### Appendix 1. Integrated Inventory for Initial Forecasting

This table is shown the value of  $m$ ,  $Q$ , and  $\theta$  are already constant  $TRC$  with Lead time,  $i=0$

<i>Iteration</i>	<i>m</i>	<i>Q</i>	<i>θ</i>	<i>TRC(Q<sub>i</sub>, m<sub>i</sub>, θ<sub>i</sub>, L<sub>i</sub>)</i>
1	1.00070	531.26057	0.000002241207	1367866.36923759
2	1.82296	531.26057	0.000001230291	1358147.44264763
3	1.83386	531.26057	0.000001222978	1358146.51751119
4	1.83394	531.26057	0.000001222925	1358146.51746220
5	1.83394	531.26057	0.000001222925	1358146.51746220

*TRC with Lead time, i=1*

<i>Iteration</i>	<i>m</i>	<i>Q</i>	<i>θ</i>	<i>TRC(Q<sub>i</sub>, m<sub>i</sub>, θ<sub>i</sub>, L<sub>i</sub>)</i>
1	1.35121	725.23272	0.0000012158844	1829296.33475
2	1.34349	725.23272	0.0000012228735	1829295.47964
3	1.34343	725.23272	0.0000012229242	1829295.47959
4	1.34343	725.23272	0.0000012229246	1829295.47959
5	1.34343	725.23272	0.0000012229246	1829295.47959

*TRC with Lead time, i=2*

<i>Iteration</i>	<i>m</i>	<i>Q</i>	<i>θ</i>	<i>TRC(Q<sub>i</sub>, m<sub>i</sub>, θ<sub>i</sub>, L<sub>i</sub>)</i>
1	1.02635814	951.49634	0.000001220076540	2378438.09568
2	1.02398515	951.49634	0.000001222903947	2378437.95621
3	1.02396797	951.49634	0.000001222924461	2378437.95621
4	1.02396785	951.49634	0.000001222924610	2378437.95621
5	1.02396785	951.49634	0.000001222924611	2378437.95621
6	1.02396785	951.49634	0.000001222924611	2378437.95621

*TRC with Lead time, i=3*

<i>Iteration</i>	<i>m</i>	<i>Q</i>	<i>θ</i>	<i>TRC(Q<sub>i</sub>, m<sub>i</sub>, θ<sub>i</sub>, L<sub>i</sub>)</i>
1	0.97444971	1001.53137	0.000001220869198	2499656.6002156200
2	0.97282378	1001.53137	0.000001222909698	2499656.5276256000
3	0.97281201	1001.53137	0.000001222924503	2499656.5276217800
4	0.97281192	1001.53137	0.000001222924610	2499656.5276217800
5	0.97281192	1001.53137	0.000001222924611	2499656.5276217800
6	0.97281192	1001.53137	0.000001222924611	2499656.5276217800

TRC with Lead time,  $i=4$

Iteration	$m$	$Q$	$\theta$	TRC( $Q_i, m_i, \theta_i, L_i$ )
1	0.92963109	1051.91878	0.000001218429149	2621698.04887566000
2	0.92623847	1051.91878	0.000001222891994	2621697.70094386000
3	0.92621395	1051.91878	0.000001222924374	2621697.70092561000
4	0.92621377	1051.91878	0.000001222924609	2621697.70092561000
5	0.92621377	1051.91878	0.000001222924611	2621697.70092561000
6	0.92621377	1051.91878	0.000001222924611	2621697.70092561000

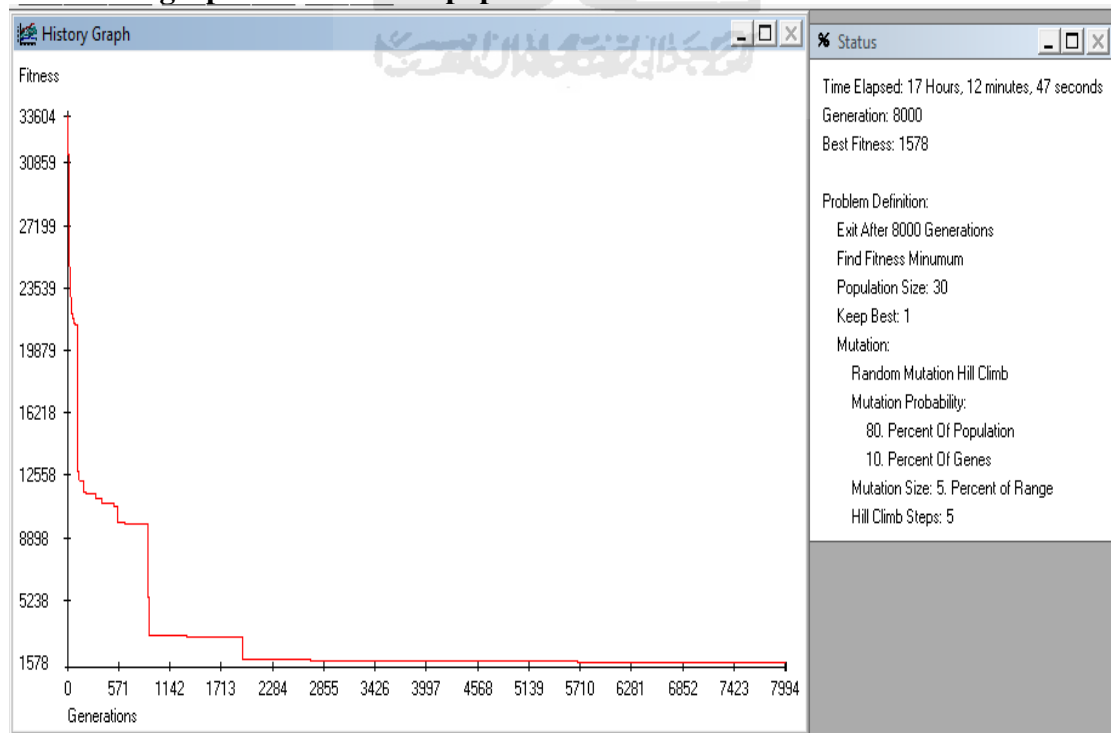
## Appendix 2. Summaries of the solution procedure of integrated inventory for $m, Q, \theta_i$ , and $L$ for Initial Forecasting

Table 4.18 Summaries of the solution procedure for  $m, Q, \theta_i$ , and  $L$  for initial forecasting

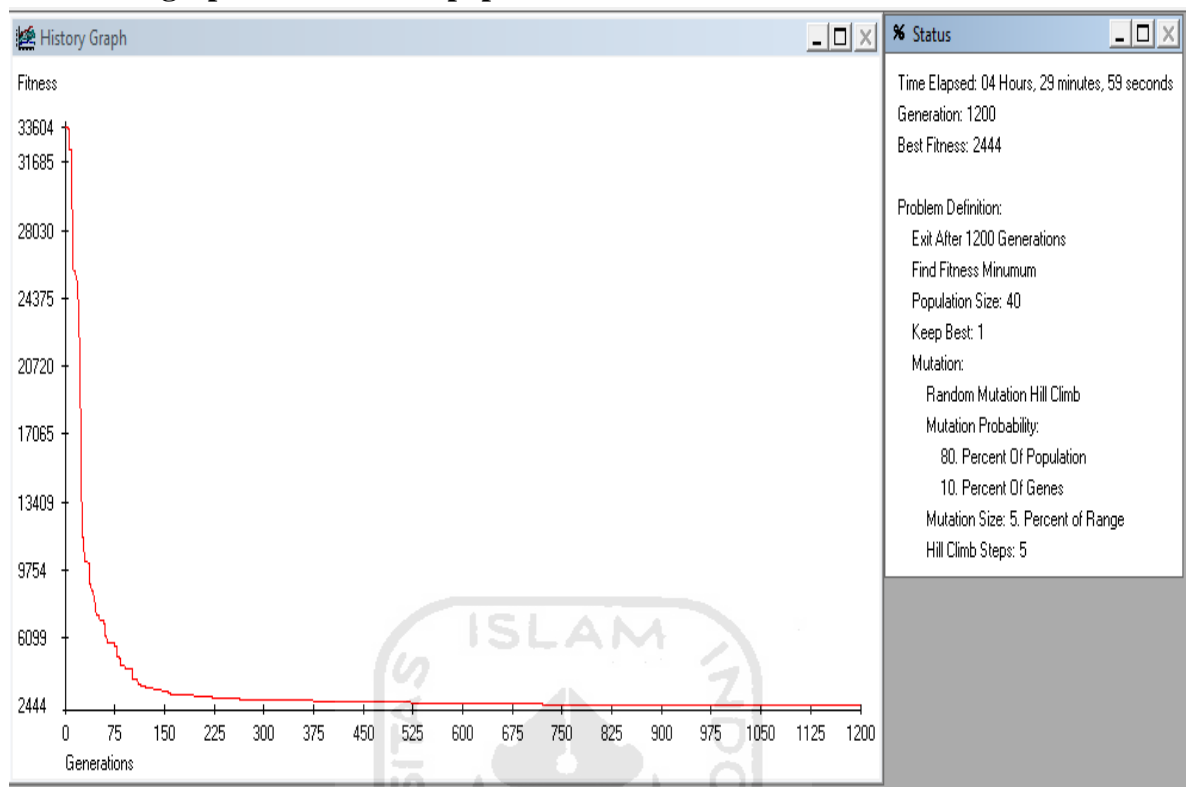
$i$	$L_i$	$m_i$	$Q_i$	$\theta_i$	TRC( $Q_i, m_i, \theta_i, L_i$ )
0	14	2	531	0.000001222925	1,358,147
1	12	2	725	0.000001222925	1,829,295
2	9	2	951	0.000001222925	2,378,438
3	8	1	1002	0.000001222925	2,499,657
4	7	1	1052	0.000001222925	2,621,698

## Appendix 3. GA graph and Status for Population 30, 40, and 50

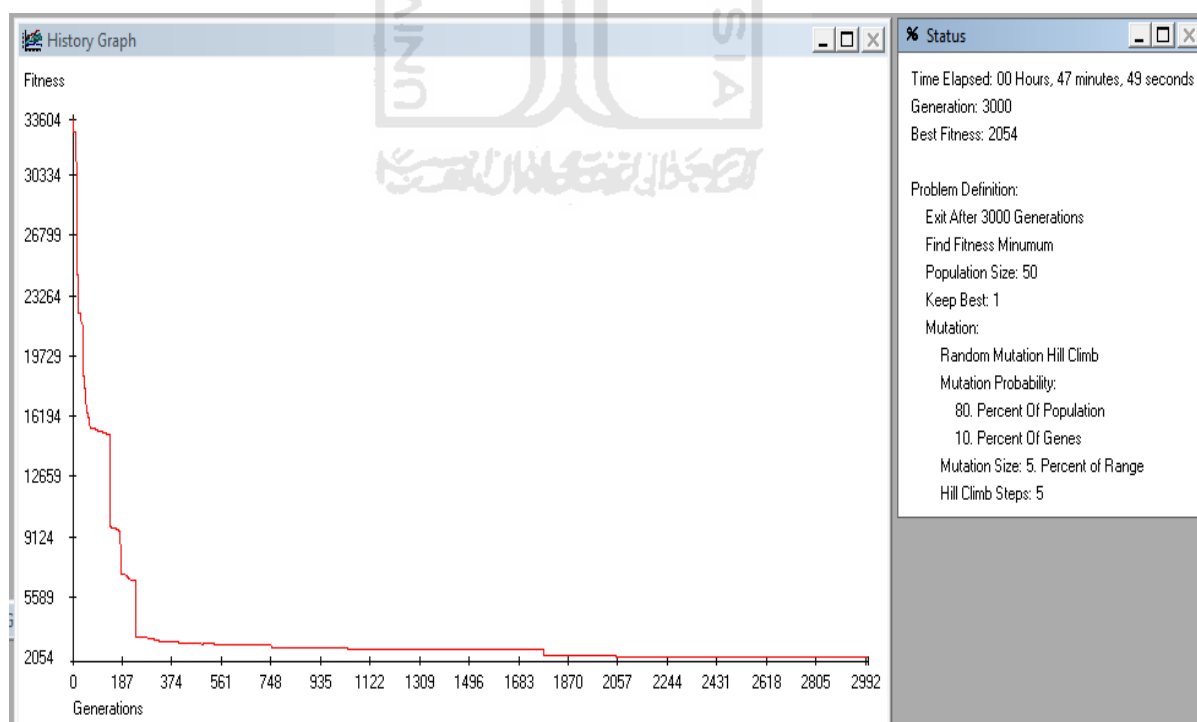
### 1. GA graph and status for population 30



## 2. GA graph and status for population 40



## 3. GA graph and status for population 50



## Appendix 4 summary of fuzzy calculation for population 30, 40, and 50

Month	D	inv	TP	Rule	a cut	Demand	Inventor	Then Z	Forecast	Error <sup>2</sup>	
1	960	62	1022	R1	0.11358	960	62	509.064	57.8179	1024.15	4.60497
				R2	0.84581	960	62	1108.65	937.711		
				R3	0	960	62	966.259	0		
				R4	0.00481	960	62	272.886	1.312		
				R5	0.0358	960	62	762.622	27.3052		
				R6	0	960	62	894.73	0		
				R7	0	960	62	159.462	0		
				R8	0	960	62	503.101	0		
				R9	0	960	62	1486.76	0		
2	1026	238	1202	R1	0.00	1026	238	886.847	0.00283	1145.62	3178.54
				R2	0.37	1026	238	1418.77	529.331		
				R3	0.00	1026	238	1033.29	0		
				R4	0.00	1026	238	489.342	0.00262		
				R5	0.63	1026	238	983.069	616.285		
				R6	0.00	1026	238	1107.77	0		
				R7	0.00	1026	238	356.567	0		
				R8	0.00	1026	238	638.76	0		
				R9	0.00	1026	238	1650.97	0		
12	1745	315	1802	R1	0.00	1745	315	1327.65	0	1799.25	7.5706
				R2	0.00	1745	315	2290.72	0		
				R3	0.12	1745	315	1757.03	204.856		
				R4	0.00	1745	315	727.471	0		
				R5	0.00	1745	315	1582.73	0		
				R6	0.88	1745	315	1804.82	1594.39		
				R7	0.00	1745	315	508.505	0		
				R8	0.00	1745	315	1033.19	0		
				R9	0.00	1745	315	2775.18	0		

Summary of fuzzy logic for population 30



Month	D	inv	TP	Rule	a cut	Demand	Inventoi	Then Z	Forecast	Error <sup>2</sup>	
1	960	62	1022	R1	0.1508	960	62	307.063	46.3045	1020.56	2.07325
				R2	0.31501	960	62	1440.62	453.818		
				R3	0	960	62	1800.28	0		
				R4	0.17293	960	62	415.338	71.8256		
				R5	0.36125	960	62	1241.82	448.612		
				R6	0	960	62	961.393	0		
				R7	0	960	62	1607.12	0		
				R8	0	960	62	545.817	0		
				R9	0	960	62	706.587	0		
Month	D	inv	TP	Rule	a cut	Demand	Inventoi	Then Z	Forecast	Error <sup>2</sup>	
2	1026	238	1202	R1	0	1026	238	332.643	0	1082.31	14326.4
				R2	0	1026	238	1691.37	0		
				R3	0	1026	238	2078.1	0		
				R4	0.17768	1026	238	446.76	79.3783		
				R5	0.48837	1026	238	1407.49	687.382		
				R6	0	1026	238	1197.73	0		
				R7	0.08908	1026	238	1720.53	153.273		
				R8	0.24487	1026	238	662.702	162.273		
				R9	0	1026	238	1082.42	0		
...											
...											
Month	D	inv	TP	Rule	a cut	Demand	Inventoi	Then Z	Forecast	Error <sup>2</sup>	
12	1745	315	1802	R1	0	1745	315	563.401	0	1802.36	0.13225
				R2	0	1745	315	2796.02	0		
				R3	0	1745	315	3453.43	0		
				R4	0	1745	315	758.122	0		
				R5	0.03893	1745	315	2351.64	91.5609		
				R6	0.46403	1745	315	1947.12	903.527		
				R7	0	1745	315	2924.67	0		
				R8	0.03848	1745	315	1084.21	41.7155		
				R9	0.45856	1745	315	1669.49	765.56		

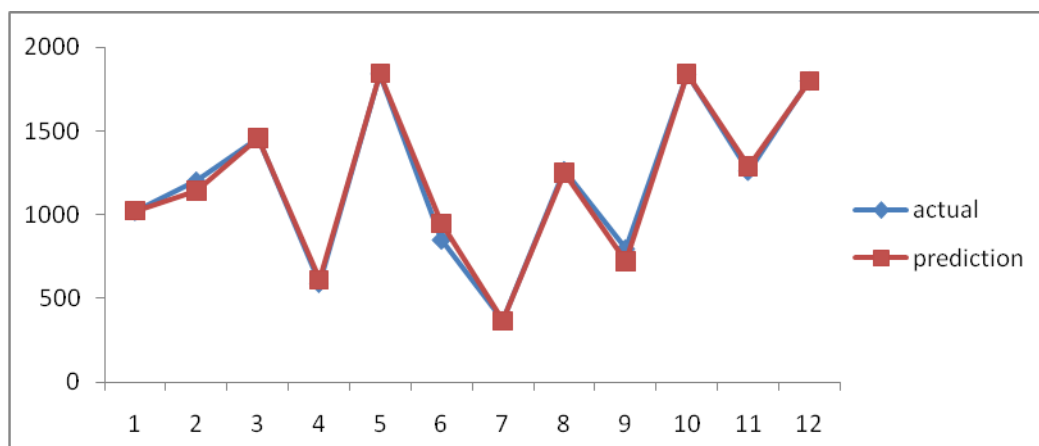
Summary of fuzzy logic for population 40

Month	D	inv	TP	Rule	a cut	Demand	Inventory	Then Z	Forecast	Error <sup>2</sup>	
1	960	62	1022	R1	0.1508	960	62	307.063	46.3045	1020.56	2.07325
				R2	0.31501	960	62	1440.62	453.818		
				R3	0	960	62	1800.28	0		
				R4	0.17293	960	62	415.338	71.8256		
				R5	0.36125	960	62	1241.82	448.612		
				R6	0	960	62	961.393	0		
				R7	0	960	62	1607.12	0		
				R8	0	960	62	545.817	0		
				R9	0	960	62	706.587	0		
Month	D	inv	TP	Rule	a cut	Demand	Inventory	Then Z	Forecast	Error <sup>2</sup>	
2	1026	238	1202	R1	0	1026	238	332.643	0	1082.31	14326.4
				R2	0	1026	238	1691.37	0		
				R3	0	1026	238	2078.1	0		
				R4	0.17768	1026	238	446.76	79.3783		
				R5	0.48837	1026	238	1407.49	687.382		
				R6	0	1026	238	1197.73	0		
				R7	0.08908	1026	238	1720.53	153.273		
				R8	0.24487	1026	238	662.702	162.273		
				R9	0	1026	238	1082.42	0		
....											
....											
Month	D	inv	TP	Rule	a cut	Demand	Inventory	Then Z	Forecast	Error <sup>2</sup>	
12	1745	315	1802	R1	0	1745	315	563.401	0	1802.36	0.13225
				R2	0	1745	315	2796.02	0		
				R3	0	1745	315	3453.43	0		
				R4	0	1745	315	758.122	0		
				R5	0.03893	1745	315	2351.64	91.5609		
				R6	0.46403	1745	315	1947.12	903.527		
				R7	0	1745	315	2924.67	0		
				R8	0.03848	1745	315	1084.21	41.7155		
				R9	0.45856	1745	315	1669.49	765.56		

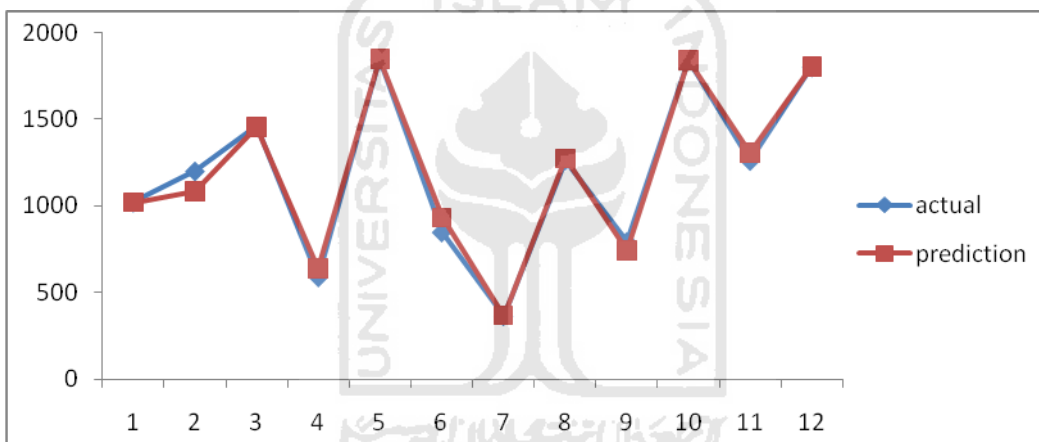
Summary of fuzzy logic for population 50

### Appendix 5. Actual and prediction graph for population 30, 40, and 50

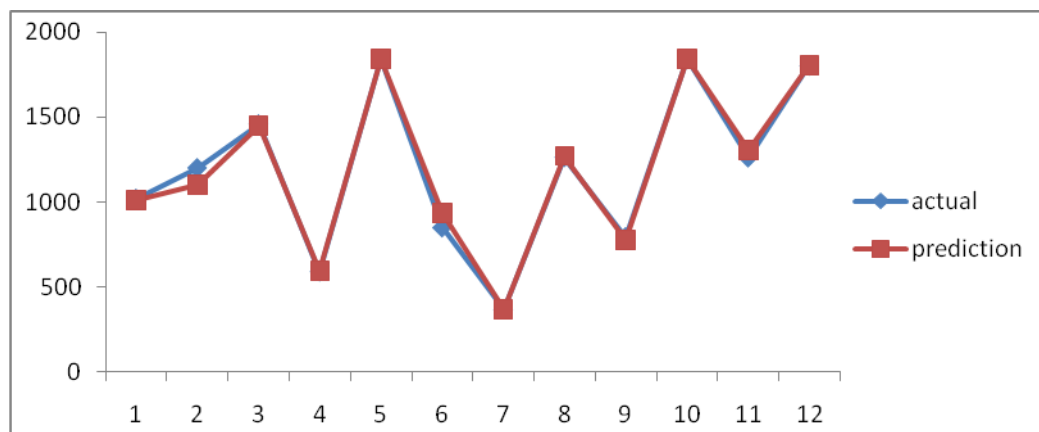
Actual and prediction graph for population 30



Actual and prediction graph for population 40



Actual and prediction graph for population 50



**Appendix 6. Summaries of the solution procedure of integrated inventory for  $m, Q, \theta_i$ , and  $L$  for population 30, 40 and 50**

Summaries of the solution procedure for  $m, Q, \theta_i$ , and  $L$  for population 30

$i$	$L_i$	$m_i$	$Q_i$	$\theta_i$	$TRC(Q_i, m_i, \theta_i, L_i)$
0	14	3.00000	522	0.000000866614186719	1367435
1	12	2.00000	712	0.000000866614186515	1847347
2	9	2.00000000	934	0.000000866614186581	2406705
3	8	2.00000000	983	0.000000866614186584	2530179
4	7	2.00000000	1033	0.000000866614186584	2654491

Summaries of the solution procedure for  $m, Q, \theta_i$ , and  $L$  for population 40

$i$	$L_i$	$m_i$	$Q_i$	$\theta_i$	$TRC(Q_i, m_i, \theta_i, L_i)$
0	14	3.00000	522	0.000000871804178174	1367487
1	12	2.00000	712	0.000000871804177976	1847339
2	9	2.00000000	934	0.000000871804178040	2406626
3	8	2.00000000	983	0.000000871804178044	2530085
4	7	2.00000000	1033	0.000000871804178044	2654381

Summaries of the solution procedure for  $m, Q, \theta_i$ , and  $L$  for population 50

$i$	$L_i$	$m_i$	$Q_i$	$\theta_i$	$TRC(Q_i, m_i, \theta_i, L_i)$
0	14	3.00000	522	0.000000875443105640	1367158
1	12	2.00000	712	0.000000875443105445	1846836
2	9	2.00000000	935	0.000000875443105508	2405922
3	8	2.00000000	984	0.000000875443105512	2529336
4	7	2.00000000	1033	0.000000875443105512	2653588