COMPARISON OF ARTIFICIAL NEURAL NETWORK AND SUPPORT VECTOR MACHINE ON PRODUCTION QUANTITY PREDICTION

THESIS

Submitted to International Program
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Muhammad Ridwan Andi Purnomo., ST., M.Sc., Ph.D

THIS THESIS IS DEDICATED TO:

My family and all my friends who support me... I’m nothing without you

MOTTO

إِنَّ ٱللَّهَ يُدۡخِلُ ٱلَّذِينَ ءَامَنُواْ وَعَمِلُواْ ٱلصَّٰلِحَٰتِ جَنَّٰتٖ تَجۡرِي
مِن تَحۡتِهَا ٱلۡأَنۡهَٰرُۚ إِنَّ ٱللَّهَ يَفۡعَلُ مَا يُرِيدُ

"Indeed, Allah will admit those who believe and do righteous deeds to gardens beneath which rivers flow. Indeed, Allah does what He intends" (QS. Al- Haj : 14)

فَٱذۡكُرُونِيٓ أَذۡكُرۡكُمۡ وَٱشۡكُرُواْ لِي وَلَا تَكۡفُرُونِ

"So remember Me; I will remember you. And be grateful to Me and do not deny Me" (QS. Al-Baqarah : 152)

إِنِّي تَوَكَّلۡتُ عَلَى ٱللَّهِ رَبِّي وَرَبِّكُمۚ مَّا مِن دَآبَّةٍ إِلَّا هُوَ ءَاخِذُۢ بِنَاصِيَتِهَآۚ إِنَّ
رَبِّي عَلَىٰ صِرَٰطٖ مُّسۡتَقِيمٖ

"Indeed, I have relied upon Allah, my Lord and your Lord. There is no creature but that He holds its forelock. Indeed, my Lord is on a path [that is] straight"
(QS. Hud: 56)

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ABSTRACT

This research presents the comparison of Neural Network Back Propagation (NNBP) model and Support Vector Machine (SVM) for predicting production quantity. This model is built based on input variables that affect the determination of production quantity which include demand, setup costs, production, material costs, holding costs, transportation costs. The performance of NNBP and SVM can be anlyzed using Root Mean Square Error (RMSE). The experiment is performed by optimizing the parameter of NNBP model and SVM by trial and error to find the smallest error between actual and predicted. The proposed models are examined using primary dataset that was collected from Iron Casting Manufacturing in Klaten, Indonesia.This data set is split into training data 60% and testing data 40%. Meanwhile, statistical analysis considers the significant difference between the proposed models. Experimental results show that NNBP provides smaller RMSE than an SVM model.The proposed model contributes not only to update the original instrument, but also applicable and beneficial for the industry, particularly in deciding effective inventory replenishment decision on production quantity.

Keywords: Neural Network, Support Vector Machines, Prediction, RMSE

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CHAPTER I

INTRODUCTION

1.1 Background

In the global competition now, the company has been intensifying every aspect in organizations such as the face of new products, innovation, technology development, and advances in the industry and information (Karim et al, 2008). Most industries try to configure their business to improve manufacturing processes, operations, and provide high quality product. Organizations in the company must make good decisions to continue their business more effectively and efficiently in all activities of the supply chain as well as the process of providing in the near future for the best quality products (Karim and Arif, 2013). In specific, industries need to consider the effective decision that able to increase business performance.

The existence of computing technology has been linked to deal with the complex problems in the industry. This refers to a collection of tools or techniques to help in decision making and improving the business performance. Nonetheless, before the implementation of computing technology, it is important to first configure the decision level of organization. Existing problems in the industry have been supported by computing technologies that can be used to make decisions more efficiently and effectively. One of pointing problems in this resarch is the implementation of computing technology on inventory problems.

Decision making is a general concept that occurs in various situations. Decision making is the process of mentality, which involves assessment on several options or alternatives, to choose one decisions, so that the best and appropriate decision fulfils the purpose or objectives of the decision maker. Figure 1.1 shows an organization level decision. There are three levels of management structure to make a decision, a long period of time decision is a strategic decision, the middle period time is tactical decision and short-term period time is operational decision(Bohanec, 2009).

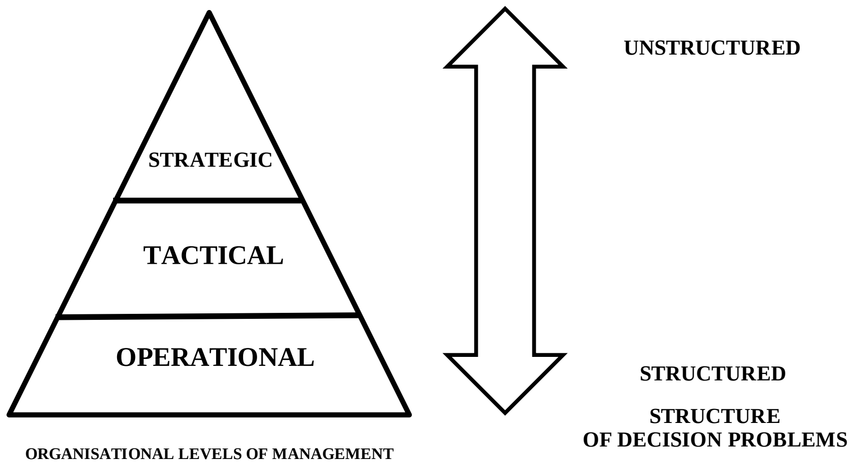

Figure 1.1 Decision making

Strategic decisions affect the entire organization, or the major part of it, for a long period of time. In most cases, they are made by the top levels management of the organization. Tactical decisions affect part of an organization for a limited time in the future. Decisions are made by tactical general middle managers and take place in the context of previous strategic decision. Operational decisions affect only the current events in an organization; they have no or very limited impact for a short time. Operational decisions are usually made by lower-level managers or non-managerial personnel. They are generally structured or semi-structured.

These problems are associated with production planning problems that aimed to determine the period where production should take place and the quantities to be produced. Therefore, determination of production quantity for inventory replenishment decision is categorized as tactical decision in order to satisfy demand. Bad decisions in a number of productions will affect the sizing of many imbalances also influence the costs charged for booking in shipping supplies production (Achmad, 2012).

Managing inventory is a tactical decision making in industrial organization. Managing inventory is no longer a new issue . However, a decision making that associated with inventory indeed an issue for production manager which must be handled seriously, since the inventory represents about 20 to 60 percents of its total assets in companies manufacturing (Giannoccaro et.al, 2003). Most industries use push-inventory system, where they keep producing the products or produce based on the demand forecast. Hence, the problem occurred when the actual demands do not match to the forecasted demand (Hirakawa, 1996; Bonney et al., 1999;Gutierrez et al., 2008).Therefore, many researchers have studied the possible factors that cause it. (Razmi et.al, 1998).

Modelling is one ways ton solve the problem. Solution procedure involves the preparation and application of model supplies. Most problems, including models and procedures, preparation solution (Cárdenas, 2010; Varberg et.al, 2007). If the model is not defined properly, it will cause difficulties for the researchers and practitioners for understanding the model (Chung, 2013). In a tactical decision, there is a technique called as Economic Production Quantity (EPQ). Many companies use the inventory model of the EPQ to manage their inventory, which is the raw material procurement activities or specific components that are mass-produced are used alone as the sub-components of a finished product by the company. EPQ Model facing a setup fee (S) to each lot production and shipped it after the completion of a batch production, which was recognized as the policy of lot for lot. Companies often have to decide whether it is more effective (cost) to order in large quantities or small within commonly (Mendoza and Ventura, 2009). However, all previous studies of inventory models that have unrealistic assumptions such as: constant demand, the purchase price is constant, the setup of deterministic, no stock out and there is no shortage of items, that become assumption in the model supplies is not realistic when implemented in the real world of manufacturing (Paul and Azaeem, 2011).

In order to release the assumptions of the inventory model, this research proposes an implementation of computing technology to solve the complex problems in inventory management. Since the variables that influence on business' cost is always fluctuating, hence computing technology is used to predict an effective decision based on historical data. The computing technology techniques are used to develop prediction model will further be discussed.Therefore, the weakness of the model supplies in determining the amount of production can be performed with other methods such as the model predictions.

Recently, the development of prediction modelling using Artificial Neural Network (ANN) is widely used in the model predictions. Because the ability of the artificial neural network as predictive model, it can help the production manager to determine and make some decisions on production capacity so as to determine the amount of inventory and reduce costs. Artificial Neural Networks (ANN) capable of modelling very complex systems and nonlinear with many interrelated parameters, and does not require detailed information about the physical parameters of the system. However, it takes available data to predict the relationship between input and output parameters. Various types of ANN, namely neural network backpropagation (NNBP) is applied widely because it has good resistance and fault tolerance, and capable of approaching any continuous function(Tan et.al, 2012). According to Adineh et.al, (2008) the advantages of ANN in the predictions include the following:

(1) A high degree of calculation

(2) The ability to learn through presentations

(3) Predictive patterns is not known

(4) Flexibility in many patterns.

Based on this capability, the ANN can be used for prediction of quantity production.Other methods that can be used in prediction is the Support Vector Machine (SVM). SVM is a new machine of learning methods based on statistical learning theory, which solves the problem of overfitting and has excellent generalization capabilities in small sample situations. The practicality of SVM is affected because of the difficulty in selecting the appropriate SVM parameters (Coussement and Van, 2008). SVM aims to produce a model for predicting the value of target sample test in the set data is given only as an attribute (Renukadevi, 2013). SVM Model is able to predict with good accuracy in many cases. However, one of the main reasons for the SVM popularity is the ability to model complex nonlinear relationship. The purpose of the SVM is to produce models (based on data training) that predicts the values of a data target test, only accommodated by the attributes of the test data.

In this research, an ANN and SVM are suggested for prediction of quantity production. Researchers will analyse in depth about the ability comparison between ANN and SVM for production prediction.

1.2 Research Question

Based on the reasoning in the background research, research question can be formulated and constructed as follows:

1. What is the prediction value for production quantity using an artificial neural network model?
2. What is the prediction value for production quantity using support vector machine model?

1.3 Problem Limitation

The research requires a limitation. Therefore, the limitations are set as follows:

1. This research was conducted in the CV. Huda Karya, Klaten, Indonesia.
2. This research is focused to predict the quantity of production by using artificial neural network method and support vector machine.
3. This research focuses on a single product.
4. The dataset focus on the production lines include demand, setup cost, production, material cost, holding cost, transportation cost and production quantity.
5. The performance is evaluated using Root Mean Square Error (RMSE).
6. The quantity of production is predicted using RapidMiner® software.

1.4 Research Objectives

The purposes of this research are:

1. To predict values of production quantity using an artificial neural network model.
2. To predict values of production quantity using support vector machine model.

1.5 Significance of Research

The significance of this research has been intended to provide a potential solution to the issues related to inventory, which include the following significant outputs:

1. Prediction model for Production Quantity.
2. Comparative analysis between accuracy of prediction among proposed models for production quantity prediction.

1.6 Systematical of Writing Thesis

CHAPTER II **LITERATURE REVIEW**

This chapter will present the research studies both deductive and inductive. Inductive studies are designated to determine previous research literature studies. Additionally, it also describes the background of the theory.

CHAPTER III **RESEARCH METHODOLOGY**

This chapter concerns on the research design of research methodology for constructing and developing the models, hardware and software, procedures. Research data will be assessed and the analyzed for the development of artificial neural network model and support vector machine model for production quantity prediction.

CHAPTER IV **EXPERIMENT RESULT**

This chapter presents the experimentation and testing methods were used to develop an artificial neural network and support vector machine.

CHAPTER V **DISCUSSION**

This chapter discusses about the analysis result of the experimentation on artificial neural network and support vector machine model.

CHAPTER VI **CONCLUSION AND SUGGESTION**

This chapter presents conclusions of the research results, research contribution and suggestions for further research.

REFERENCES

APPENDIX

CHAPTER II

LITERATURE REVIEW

This chapter will be present the literature study of the research which are deductive and inductive. Inductive studies are designated to determine previous research literature studies. Additionally, it also describes the background of the theory.

2.1 Previous Research

Inventory management is an important concern for all managers in all types of businesses. Duell, (2001) explained that there were several pressures for low and high inventories that have to be balanced to achieve the "optimal" inventory management strategy. Pressures for low inventories include, but are not limited to: holding costs, interest or opportunity costs, storage and handling costs, taxes, insurance, and shrinkage costs. Pressures for high inventories include, but are not limited to: customer service (backorders and stockouts), ordering costs, setup costs, labor and equipment utilization, transportation costs, and quantity discounts.

Economic Ordering Quantity (EOQ) provides the most practical cost reduction strategy for inventory management. The EOQ model considers the tradeoff between ordering cost and storage cost in choosing the quantity to be used in replenishing item inventories. A larger order-quantity reduces ordering frequency, and hence ordering cost/ month, but requires holding a larger average inventory, which increases storage (holding) cost/month (Schwarz, 2008). The basic EOQ model is used to identify the order size that will minimize the sum of annual cost of inventory holding and fixed setup in order to place an order. The importance of EOQ model not only viewed from a historical perspective, but also derived from another model, which is designed to overcome a different situation based on this model. Meanwhile, Taft, (1918) presented Economic Production Quantity (EPQ) model to assist the supplier in determining optimal production quantity.

Some studies on EPQ model consider production processes, inspection errors, planned backorders, and sales return (Hsu and Hsu, 2013). They develop this model in order to get solution for the optimal production lot size and the maximum shortage level. Noorollahiet.al., (2012) developed EPQ model considering realistic condition in imperfect production system that generated defect product randomly for determining economic production quantity. However, all previous inventory models show that all model always developed based on unrealistic assumption in real system because of changing due to market fluctuation on business area (Wazed et al., 2009).

Artificial Neural Networks (ANN) can be defined as a model of reasoning based on the human brain. The brain consists of nerve cells called neurons that are intertwined. The human brain consists of almost 10 billion neurons and 60 trillion synapses, the connections between them (Negnevitsky, 2005). Developments in the use of predictive modeling of Artificial Neural Network (ANN) is one that is widely used in model predictions of economics, accounting and finance, business and marketing, health and medicine, engineering and manufacturing (Paliwal and Kumar, 2009).

ANN has been used by some researchers to develop applications to help them in making financial decisions. A simple ANN model do a pretty good job in predicting price movements in the stock market, by buying or selling the prediction accuracy is much higher than the traditional models (Weck man et.al, 2008). Over the years, a variety of predictive models in the industry has strengthened, largely due to the effectiveness and better predictive ability. An inventory of the problems can be overcomed by using Artificial Intelligence (AI) to assist the production manager in order to solve problems in the real world for planning production (Noorollahi et.al, 2012). The ANN model is able to solve the problem on the ABC classification to keep manufacturing unit shares (Partovi and Anandarajan, 2002). ANN model is also used for solving problems in scheduling shop floor employment in a flexible manufacturing system (Yildirim et.al, 2006).

SVM has expanded to solve non-linear regression estimation, called as SVM regression (SVR). The SVR has been applied to various fields such as optimal control and prediction interval regression analysis (Abakar and Yu, 2014). SVM has been widely used in pattern of recognition and regression. SVM has a comparable computing efficiency and good ability to generalize (Akram et.al, 2014).

SVM has a parameter called kernel methods. Kernel methods are algorithms that depend on data only through the dot product. When this happens, the dot product can be replaced with a kernel function that calculates the dot product in some spaces feature dimensions that may be high. This has two advantages: first, the ability to produce non-linear decision boundaries using methods which designed for linear groups. Second, the use of a kernel function allows the user to apply classification data that do not have clarity remains in the dimension of a vector space.

Many researchers using the application of SVM in prediction. Using the algorithm of SVM prediction of tunnel convergence during excavation (Mahdevari et.al, 2013). Nejatian et.al, (2014) studied a natural gas flow prediction using support vector machine algorithm. Saruta et.al,(2013) applied predictive model for content and yield of rice protein by using support vector machines. Li et.al, (2011) was applied time series mining subsidence prediction based on the SVM. Predictions must be robust to variations in the input data that is collected as a representative sample in the actual field. To improve the prediction resistance, it is reasonable to predict the class with a range of values rather than a specific figure.

2.2 Background Theory

2.2.1 Inventory

According to Stevenson, (2011) inventory is a stock or store of goods. In manufacturing, inventory carries supplies of raw materials, purchased parts, partially competed items, and finished goods, as well as spare parts for machines, tools, and other supplies.

2.2.2 Functions of Inventory

Inventories serve a number of functions. Among them, the most important are explained as follows:

1. To meet anticipated demand
2. To smooth production requirements
3. To decouple components of the production distribution system
4. To protect against stock outs
5. To take advantage of order cycles
6. To hedge against price increases or to take advantage of quantity discounts
7. To permit operations

2.2.3 Component of Inventory Models

The components of inventory models include the various types of costs. One straight forward inventory criteria are the minimization of cost:

A. Ordering or Setup Cost

An ordering cost is the cost incurred whenever an order is made. It is independent from the quantity being ordered. It is primarily a clerical and administrative nature. Typical elements of this cost include the cost associated with processing, labor, overhead (telephone, postage, etc.), and transport (delivery charges). In other environments, the setup cost could be termed clerical and administrative cost.

B. Carrying or Holding Cost

The holding cost represents all the costs associated with the storage of the inventory until it is sold or used. Included are the cost of insurance, capital, space, protection and taxes attributed to the storage. It is proportional to the amount of an inventory and the time over which it is held. It is unavoidable, but with good management it can be reduced.

C. Unit Purchasing Cost

This is the variable associated with purchasing a single unit. Typically, the unit purchasing cost includes the cost of raw materials associated with purchasing or producing a single unit. This cost may be a constant for all quantities, or it may vary with quantity purchased or produced.

D. Transportation Cost

Transportation is related to the movement of goods from one location to another. The company incurs a cost to do transportation activities. The warehouse always has enough trucks and inventory to fill the store's replenishment requests, but any shipment requires a constant transportation time from the warehouse to the store (Cachon, 2001).

2.2.4 Economic Order Quantity Model

According toWinston, (2011) Economic Order Quantity (EOQ) modeled the method that provides the company with an order quantity. This order quantity figure is where the record of holding costs and ordering costs are minimized. By using the EOQ model, the companies can minimize the costs associated with the ordering and inventory holding.The Economic Order Quantity (EOQ) is a model that is used to calculate the optimal quantity that can be purchased or produced to minimize the cost of both the carrying inventory and the processing of purchase orders or production setup.

2.2.5 Assumptions of the Basic Economic Order Quantity Model

For the basic EOQ model, certain assumptions are required (assume that the unit of time is one year):

1. Demand is deterministic and occurs at a constant rate.
2. If an order of any size (say, q units) is placed, an ordering and setup cost K is incurred.
3. The lead time for each order is zero.

4. No shortages are allowed.
5. The cost per unit-year of holding inventory is h.

The EOQ model determines an ordering policy that minimizes the yearly sum of ordering cost, purchasing costs, and holding costs. For the models, certain assumptions must be satisfied:

A. Repetitive ordering

Repetitive ordering is the system whereby the placement of an order follows a regular fashion. For example, when a company orders bearing assemblies , then considers that the inventory is depleted later it will place another order, and so on. It contrary with one time orders.

B. Deterministic Demand

Demand is assumed to occur at a known constant rate. For example, if demand occurs at a rate of 500 units per month, then at any particular t week period, we shall have $\frac{500t}{4}$demand.

C. Constant lead time

The lead time for each order is a known constant, say L. The lead time means the length of time between placed order and its arrival. If L = 3 months, say, then after each order will arrive exactly 3 months after the order is placed.

D. Continuous ordering

An order may be placed at any time. For example, an order is placed and it will be waited till it gets to its reorder point (level prescribed by the ordering system that allows an order to be made when inventory falls to that level) before you place another order. It is contrary with the continuous ordering which is periodic, it, only reviews inventory at the end of each period and decide whether it is necessary to place an order or not at the time of review. Although the constant lead time and the constant demand assumptions may seem unrealistic, there are many situations that deterministic inventory models provide a real good approximation to reality.

2.2.6 Basic of EOQ Model

Derivation of the optimal ordering policy is made by making some simple observations. Since orders arrive instantaneously, an order should never be placed when I, the inventory level, is greater than zero. If an order is placed when $I > 0$, incurring an unnecessary holding cost. On the other hand, if $I = 0$, an order must be placed to prevent a shortage from occurring. Together, these observations show that in order to minimize yearly costs, an order must be placed whenever $I = 0$. The same policy is applied then an order is placed under the same situation ($I = 0$). This means that each time an order is placed, hence it should be ordered under the same quantity. $I = 0$ is the quantity that should be ordered . The value of q minimizes annual cost (call it q^*). TC (q) will be the total annual cost incurred if q units are ordered each time that I = 0. Note that:

TC (q) = annual cost of placing orders + annual purchasing cost + annual holding cost (2.1)

Since each order represents q units, $\frac{D}{q}$ order per year will have to be placed so that the annual demand of D units is met. Hence

$$\frac{Orderingcost}{Year} = \left(\frac{Oredering cost}{unit}\right)\left(\frac{Orders}{Year}\right) = \frac{KD}{q} \tag{2.2}$$

For all values of q, the per unit purchasing cost is p. Since purchase D units per year,

$$Purchasing\ Cost = \left(\frac{purchasing\ cost}{unit}\right)\left(\frac{units\ purchased}{year}\right) = pD \tag{2.3}$$

To compute the annual holding cost, note that if a company holds I units for a period of one year, a holding cost of (I units) (1 year) (h dollars/unit/year) = hIdollars will incurred.

Suppose that the inventory level is not constant and varies over time. If the average inventory level during a length of time T is I, the holding cost for the time period will be hTI. If I (t) is defined to be the inventory level at time t,then during the interval [0, T] the total inventory cost is given by

h (area from 0 to T under the I (t) curve) =hTI (2.4)

The reader may verify that this result holds for the two cases graphed. More formally, I (T), the average inventory level from time 0 to time T, is formulated as

$$I(t) = \frac{\int_0^T I(t)dt}{T} \tag{2.5}$$

And the total holding cost incurred between time 0 and time T is

$$\int_0^T hI(t)dt = hTI(T) \tag{2.6}$$

To determine the annual holding cost, need to examine the behavior of *I* over time. Assume that an order of size q has just arrived at time 0. Since demand occurs at a rate of *D* per year, it will take $\frac{q}{D}$ years for inventory to reach zero again. Since demand during any period of length *t* is *Dt*, the inventory level over any time interval will decline along a straight line of slope -D. When the inventory reaches zero, an order of size q is placed and arrives instantaneously, raises the inventory level back to q.

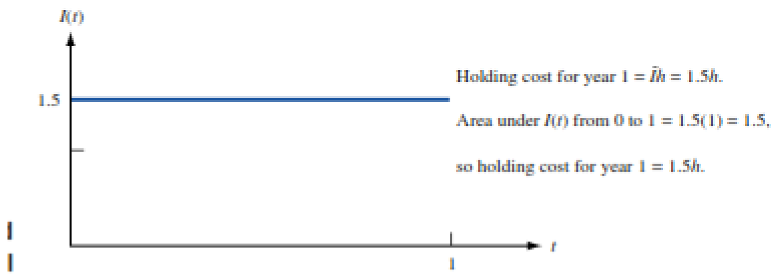

Figure 2.1 Holding Cost and Inventory Level

Simply consists of repeated cycles of length$\frac{q}{D}$. Hence, each year will contain

$$1 = \frac{D}{q} \tag{2.7}$$

The average inventory during any cycle is simply half of the maximum inventory level attained during the cycle. This result will hold in any model for which demand occurs at a constant rate and no shortages are allowed. Thus, for the model, the average inventory level during a cycle will be $\frac{q}{2}$ units. To determine the annual holding cost:

$$\text{Holding Cost} = \left(\frac{\text{Holding Cost}}{\text{Cycle}}\right)\left(\frac{\text{Cycles}}{\text{Year}}\right) \tag{2.8}$$

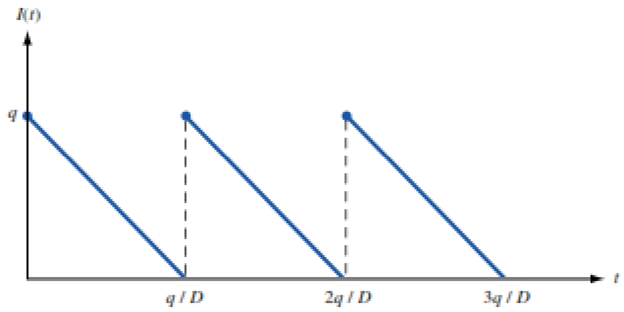

Figure 2.2Behavior of *I (t)* in the Basic EOQ Model

Since the average inventory level during each cycle is $\frac{q}{2}$ and each cycle is of length $\frac{q}{D}$

$$\frac{Holding\ cost}{Cycle} = \frac{q}{2}\left(\frac{q}{D}\right)h = \frac{q^2 h}{2D} \tag{2.9}$$

Then

$$Holding\ cost = \frac{q^2 h}{2D}\left(\frac{q}{D}\right) = \frac{hq}{2} \tag{2.10}$$

By combining ordering cost, purchasing costs, and holding costs, it is obtained:

$$TC(q) = \frac{KD}{q} + pD + \frac{hq}{2} \tag{2.11}$$

To find the value of *q* that minimizes *TC* (*q*), set *TC'* (*q*) equal to zero. This yields

$$TC'(q) = -\frac{KD}{q^2} + \frac{h}{2} = 0 \tag{2.12}$$

Equation (2.13) is satisfied for $q = \pm\,(2\frac{KD}{h})^{1/2}$. Since $q = -\,(2\frac{KD}{h})^{1/2}$ makes no sense, it is relied on the economic order quantity or EOQ

$$q = \left(\frac{2KD}{h}\right)^{1/2} \tag{2.13}$$

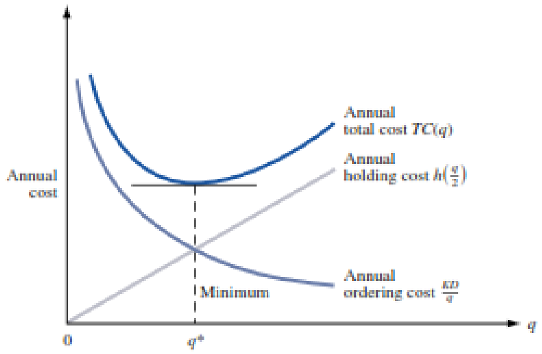

Figure 2.3 Trade-Off between Holding Cost and Ordering Cost

The following is a formula for calculating the total cost of inventory:

$$TC = \frac{D}{q}A + \frac{q}{2}H \tag{2.14}$$

$$TC = \frac{D}{Q}S + \frac{DQ}{2P}H \tag{2.15}$$

To find the optimal order quantity (q) and optimal production quantity (Q) using EOQ and EPQ, it is formulated as below:

$$q = \sqrt{\frac{2DA}{H}} \tag{2.16}$$

$$Q = \sqrt{\frac{2PS}{H}} \tag{2.17}$$

Annotation:

D = Demand	S = Setup Cost
A = Order Cost	P = Production
H = Holding Cost	Q = Economic Production Quantity
q = Economic Order Quantity	TC= Total Cost

2.2.7 Artificial Neural Network

Artificial Neural Network (ANN) is the information processing paradigm inspired by biological nervous system, such as the brain, processes information. ANN, like people, learn by example. ANN configured for specific applications, such as pattern recognition or data classification, through a learning process. A trained artificial neural network can be considered as an "expert" in the category of information that has been provided to analyze. These experts can then be used to provide projections given the new situation is interesting. Other advantages include (Rodrigues and Stevenson, 2013):

1. Adaptive learning: the ability that learns how to accomplish the task based on the data provided for the initial training or experience.
2. Self Organization: ANN can make your own organization or representation of the received information during your research time.
3. Real Time Operation: ANN calculations can be done in parallel and the specific hardware is being designed and produced to take advantage of these capabilities.
4. Fault Tolerance via Redundant Information Coding: Partial tissue damage causing a decrease in compliance performance. However, some networking capabilities can be maintained even with the major tissue damage.
5. Be able to interpret complex data.
6. It can also be used to change the patterns that are too complicated.

2.2.8 Architecture of Neuron Network Model

According to Kusumadewi, (2003) ANN has some network architectures that are often used in various applications. The ANN architecture, among others:

1. Single layer network, the network with a single layer consists of one input layer and one output layer. Each neuron / unit contained in the layer / input layer is always connected to each neuron contained in the output layer. This network then simply accepts direct input to be converted to output without having to process them through the hidden layer.
2. Multilayer networks, network with multiple layers with a certain characteristic. It has3 types of layers, namely the input layer, the output layer, and a hidden layer. Network with many layers can resolve more complex problems than a network with a single layer. However, the training process often takes a long time tend.

Artificial Neural Networks consist of input and output layers. But a hidden layer also exists between the input and output layers. Units that exist in the input layer are called as the input of the unit. In the process, the input unit is not only disseminating information to other units or channels. While the unit is in the hidden layer, output layer producing outputs. Figure 2.4 shows an artificial neural network with three layers, consisting of a layer of the input (input layer), one layer is hidden (hidden layer) and layer the output (output layer).

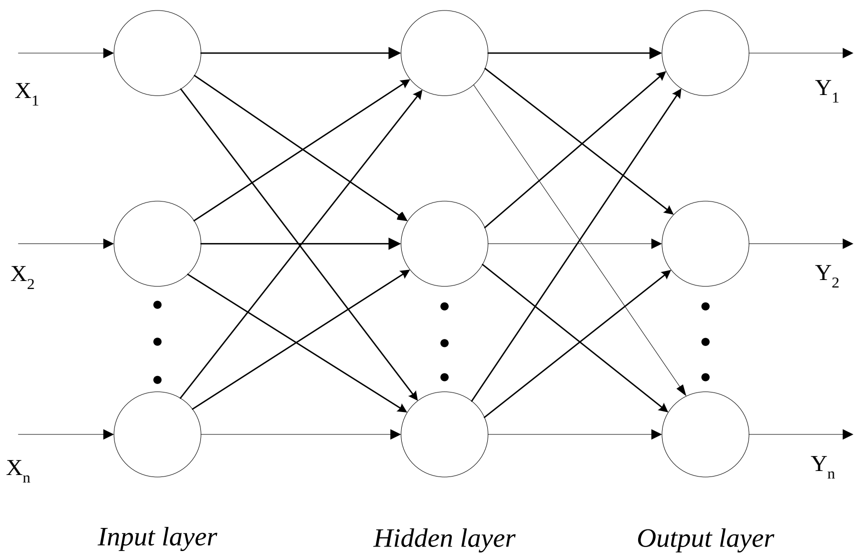

Figure 2.4Artificial Neural Networkswith threelayers

In Figure 2.4, network layer of artificial neural network consists of three layers, namely:

a. Unit Input(Input: X_1, X_2, X_n): nodes that are contained in a layer called as the input unit. They are designated to convert the input signal in a form that can be understood by the system and forwarded to the network for processing.

b. Hidden Unit (Hidden: Z_1, Z_2, Z_n): nodes that are located in this layer called as hidden units, defined as a unit that does not directly relate to the outside world (e.g., input information). It is also classified as layers that make network has a non-linear nature of the process of computing.

c. Output unit (Output: Y_1, Y_2, Y_n): This unit is for nodes that are located inside this layer yet out of the process so that it can be interpreted in accordance with the desirable cases.

The ANN activation functions are used to determine the output of the ANN calculations. There are several types of activation functions, some frequently used activation function are (Negnevitsky, 2005):

1. Step function

   Step function is used in a single-layer network to change the type of data at the input of the variable into binary form (1 and 0).

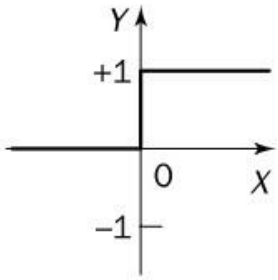

Figure 2.5 Step Function

mathematical model of the step function is as follows:

$$Y\ Step = 1, if\ X\ \geq 0 \tag{2.18}$$

or

$$Y\ Step = 0\ if\ X < 0 \quad .(2.19)$$

2. Sign Function

   In 1943, McCulloch and Pitts provided a simple idea on the activation function. This activation function works by summing the input signal is obtained by the ANN and then compare it with the threshold value, θ. If the input value is less than the threshold value, the output neurons will have a value of -1, but if the input value is more than the threshold value, the output neurons will have a value of 0.

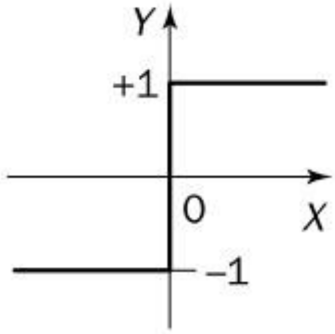

Figure2.6Sign Function

mathematical model of the sign function is as follows :

$$Y\ Step = +1, if X \geq \ \theta \tag{2.20}$$

or

$$Y\ Step = -1, if X \leq \theta \tag{2.21}$$

3. Binory Sigmoid Function

Binary sigmoid function is used to activate the output of binary data using the ANN back propagation algorithm. Binary value of the sigmoid function has a value between 0 and 1. Therefore, this function is used to ANN that require the output from 0 to 1.

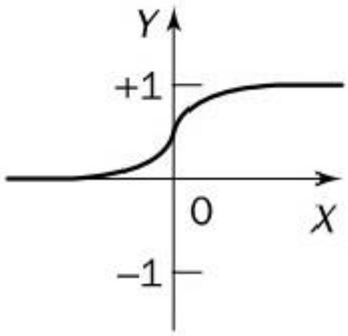

Figure 2.7Binary Sigmoid Function

mathematical model of the binary sigmoid function sign is as follows:

$$Y = f\,(x) = \frac{1}{1 + e^{-\sigma x}} \tag{2.22}$$

4. Bipolar Sigmoid Function

   This function has the same functionality with the binary sigmoid function. Only the output of this function exist at a distance of numbers -1 to 1.

$$Y = f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{2.23}$$

2.2.9 Learning Algorithm of Artificial Neural Network

All learning methods are used for the adaptive artificial neural networks can be classified into two main categories:

A. Supervised Learning

Supervised Learning captures the analogy of how a person can learn to be assisted by someone who is constantly correcting errors. As a result, the error can be reduced to a level that is relevant. In this research, both the input and the output of the ANN are determined and supplied through learning algorithms. Therefore, each time the input is given, an error will be obtained (error correction). By adjusting the weights, the error will be reduced, so that the ANN is able to produce output as close as possible to the target pattern has been set.

B. Unsupervised Learning.

In this method, the target output is unknown and the system changes according to the given input. During the learning process, the weight values are arranged in a certain range, depending on the value of a given input. The purpose of this research was to group the units are about equal in a certain.

2.2.10 Neural Network Back Propagation Supervised Learning

Backpropagation is a supervised learning algorithm and is typically used by the perceptron with a lot of layers to change the weights that connect with existing neurons in the hidden layer. Back propagation algorithm uses the output error to change the value of weight which is the weight-backward direction (backward). To get this error, advanced propagation phase (forward propagation) should be done first. When the time forward propagation is applied, the neurons are activated by using a sigmoid activation function, as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2.24}$$

Backpropagation network architecture is shown by Figure 2.8

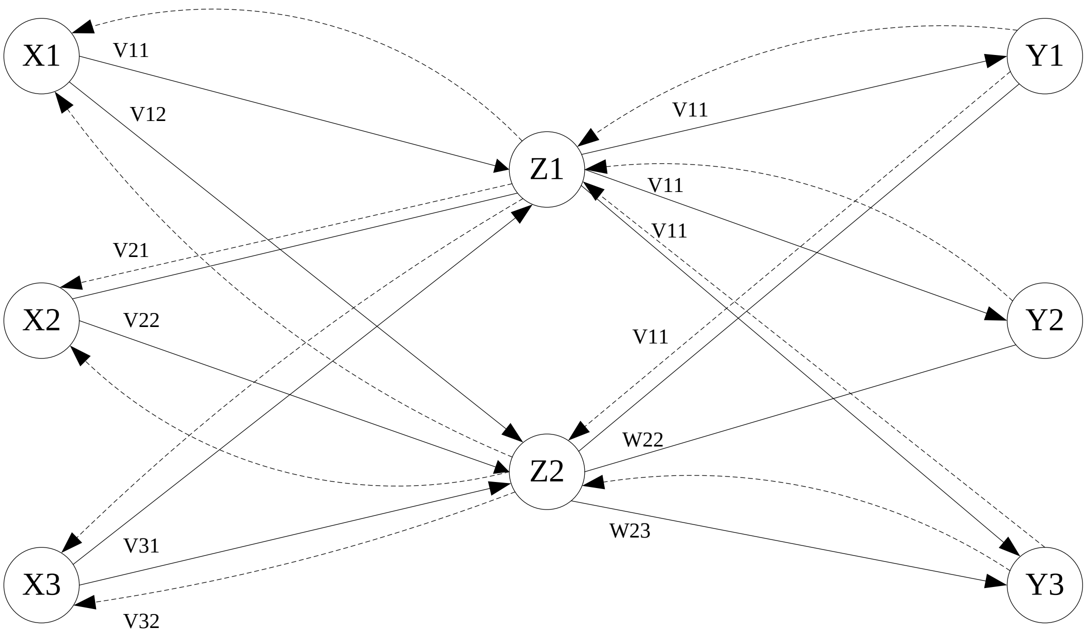

Figure 2.8 Architecture of Neural Network Back Propagation

Backpropagation algorithm:

1. Initialization of weights (taking initial weights with random values that are quite small)
2. Do the following steps during the stop condition, valued FALSE:

For each pair of input, unit elements will involve:

Forward Propagation (Feedforward):

a. Each input unit (X_i, i=1, 2,3,...n) receives input signal X_i to all units in the layer above it (the hidden layer).
b. Each hidden layer unit (Z_j, j=1, 2,3,...,p) input value is calculated using weight values

$$z_{in_j} = v_{oj} + \sum_{i=1}^{n} x_i\, v_{ij} \tag{2.25}$$

Then, output value is calculated using the activation function as follows:

$$z_j = f(z_{inj}) \tag{2.26}$$

The result of the function is sent to all units in the layer above (output units).

c. Each output unit (Y_k,k=1,2,3,....m) input value is calculated using weight values:

$$y_{in_k} = w_{ok} + \sum_{i=1}^{p} z_i\, w_{jk} \tag{2.27}$$

Then the output value is calculated using the activation function as follows:

$$y_k = f(y_{ink}) \tag{2.28}$$

Backward propagation (Backpropagation):

d. Each output unit (Yk, k=1,.., m) receives a target pattern associated with the training input pattern, and then the error information is formulated:

$$\delta_k = (t_k - y_k) f'\left(y_{\_ink}\right) \tag{2.29}$$

Next, correction weight values are calculated and will be used to update the weights of wjk:

$$\Delta w_{jk} = \alpha \delta_k z_j \tag{2.30}$$

The bias value are calculated and the correction then will be used to update the value $w0k$:

$$\Delta w_{0k} = \alpha\delta_k \quad (2.31)$$

Then value of δk is sent to the unit on the layer below.

e. Each unit of hidden layer (Zj, j=1,…, p) calculates changes in the input of the units in the layer above:

$$\delta_{in_j} = \sum_{k=1}^{m} \delta_k \, w_{jk} \quad (2.32)$$

Then the value is multiplied with derivative value of the activation function to calculate the mistake of information:

$$\delta_j = \delta\_in_j f'(z\_in_j) \quad (2.33)$$

The calculation and the correction of weight values then used to update v_{ij}:

$$\Delta v_{ij} = \alpha\delta_j x_i \quad (2.34)$$

The bias value are calculated and correction will be used to update v_{0j}:

$$\Delta v_{0j} = \alpha\delta_j \quad (2.35)$$

f. Each output unit (Yk, k=1,.., m) updated the output bias and weights (j=0,…, p):

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \quad (2.36)$$

and on each unit hidden layer (Zj, j=1,…, p) bias and weights are updated (i = 1, …., n):

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \quad (2.37)$$

g. The test is conducted whenever the stopping conditions are met. Then, the network training can be finished. The stopping conditions, commonly indicated by two ways as follows:

1. First, by limiting iteration.
2. Second, by limiting error. In the Back propagation method, Mean Square Error is used to calculate the average error between output in the training data with the output that generated by the network. In order to check stopping condition of the Mean Square Error, following steps are described as follows:

$$Mean\ Square\ Error(MSE) = \frac{1}{n}\sum_{j=1}^{n}\left(\theta_j - \theta\right)^2 \qquad (2.38)$$

A period of time (epoch) is a set round of training phase. Some epoch (iteration) is needed for training a NNBP. In this algorithm, weights are repaired after each training pattern is included. Once training is complete, then weight are saved.

2.2.11 Support Vector Machine

SVM is the formation of a hyperplane that separates two classes with the maximum distance. Support vector machine is an example of two classes of linear classification. Data for the two class learning problem consists of objects that are labeled with one of the two labels in accordance with two classes, namely considers the label 1 (positive sample) or-1 (negative sample).

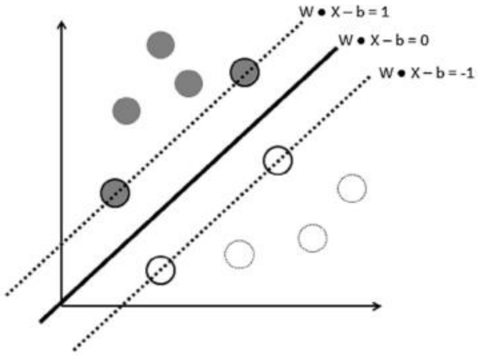

Fig 2.9 Two classes of dataset

SVM will find the maximum margin hyperplane which separates the training pattern in both classes. Sample points of nearest hyperplane defined as vectors support (Akram et al. 2014). A linear equation is represented by a Hyperplane in Eq. (2.29) where the hyperplane normal to w and b are biased.

$$w \,.\, x + b = 0 \tag{2.39}$$

Eq. (2.30) and (2.31) represent the training vector that have a variety of +1 and -1 class.

$$w \,.\, x + b = +1 \text{for class } +1 \tag{2.40}$$

$$w \,.\, x + b = -1 \text{for class } -1 \tag{2.41}$$

2.2.12 Basic of Support Vector Machine

There are three types of machine learning: unsupervised learning, reinforcement learning and supervised learning. In supervised learning, the desired results is available from the training data sets. Supervised learning is divided into two categories, namely regression (if the result is a sustainable value) and classification (if the result is the class label). Supervised learning consists of basically two phases. The first is a learning phase, where the training data used to construct a mathematical model describing the relationship between several variables. The second is the phase of the trial, in which the models used to predict the results of the test data set(Listiani 2009).

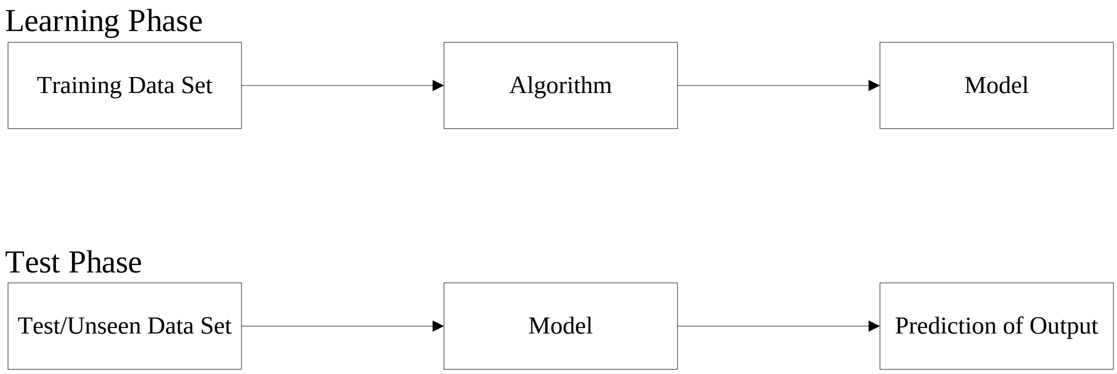

Figure 2.10 Supervised Learning Scheme

2.2.13 Support Vector Regression Supervised Learning

The SVM that used to solve regression problem is called Support Vector Regression. a training data set is provided to the learning machine. Support Vector Machine uses a novel equation called Vapnik's ε-insensitivity error function, where ε is a radius of a tube within which the regression function must lie, after the successful learning. The idea is to reduce model's complexity by tolerating errors up to a certain point. Figure 2.7 gives a visual comparison of Vapnik's ε-insensitivity error function to other two classical error functions, namely the quadratic error, as in linear regression, and the absolute error.

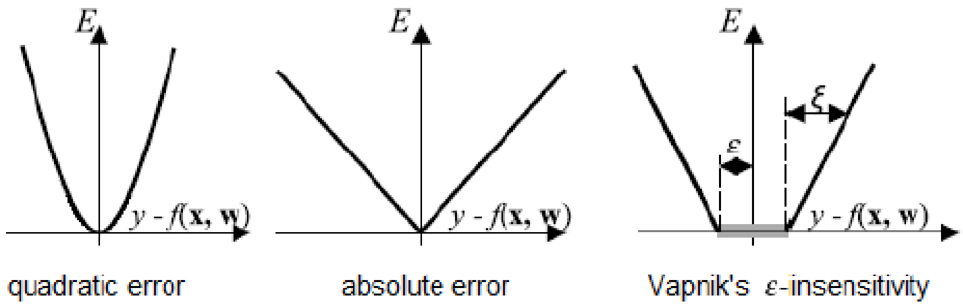

Figure 2.11 Functions of Error(Listiani 2009)

2.2.14 Kernel Functions

In general, problems in the real world (real world problem) is rarely a linear separable. Most are non linear. To resolve them, SVM is modified by inserting Kernel functions. In the non linear SVM, first data $\vec{x}$ mapped by a function $\Phi(\vec{x})$ to vector spaces which is a higher-dimensional. On a vector space, a hyperplane that separates the second class can be constructed.

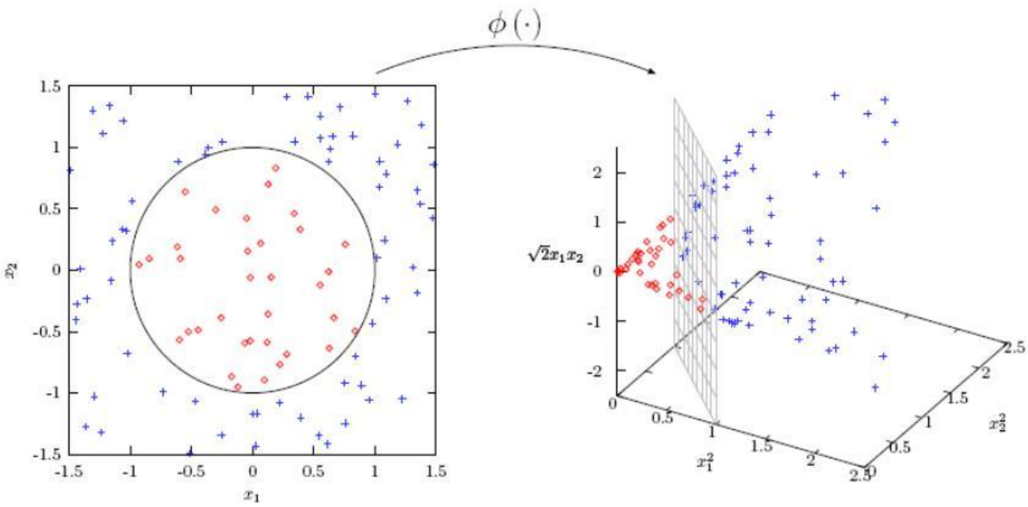

Figure 2.12 Mapping to the new high dimensional space(Listiani, 2009).

The SVM algorithm in its dual formulation depends only on the inner products of the training samples. Thus, one first maps data points using Φ, then the formula would be simply the inner products of the points in the feature space. This mapping into the hypothetical feature space is implicit, therefore it becomes feasible to use feature spaces of infinite dimensionality. The SVM learning process in finding points of support vector, depends only on the dot product of the data that has been transformed in the space of the new higher dimensional which is $\Phi(\vec{x_i}).\Phi(\vec{x_j})$. Since the General transformations Φ is unknown, then it is very difficult to be understood easily, then the dot product calculations according to the theory of functions can be replaced with Mercer kernels $K(\vec{x_i}, \vec{x_j})$ which defines implicitly transformation Φ.

This is called the Kernel Trick, formulated,

$$K(\vec{x_i}, \vec{x_j}) = \Phi(\vec{x_i}).\Phi(\vec{x_j}). \tag{2.42}$$

The Kernel trick provides various convenience, because in the process of SVM learning to determine support vector, just simply find out the kernel function that is used, and does not need to know the existence of a non-linear function Φ.

2.2.15 Characteristic of SVM

Characteristics of the SVM is described as follows:

1. In principle, it is a linear SVM classifier.
2. Pattern recognition is done by transforming the data in the input space to higher dimensional space and optimization is done on a vector space is new. This distinguishes the SVM as the solution pattern recognition from general, the optimization parameters on dimensional transformations result space is lower than the dimension of the input space.

3. Working principles of the SVM is basically only able to handle two-class classification.

2.3 Summary

This chapter discusses about inventory management, artificial neural network and support vector machine. From literature, it is expected that ANN model and SVM model can provide effective decision related to the activities of inventory replenishment. Next chapter will further discuss on the research methodology that implemented in this research.

CHAPTER III

RESEARCH METHODOLOGY

This chapter concerns on the research design of research methodology for constructing and developing the models, hardware and software and procedures. Research data will be assessed and the analyzed to be used for the development of artificial neural network model and to support vector machine model for production quantity prediction.

3.1 General Steps of Research Methodology

According to (Mitroff et.al, 1974), general steps of methodology research are thought based on the view system in solving a problem or Operation Research (OR) process as framework in this research. Based on a figure 3.1, operation research framework consisting of four components process.

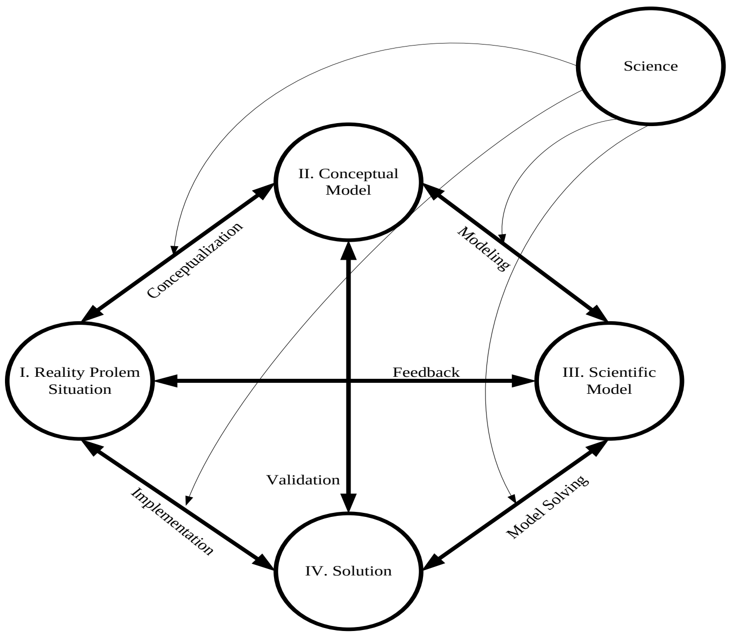

Figure 3.1 Framework on Steps Methodology (Mitroff and Sagasti, 1973)

Based on figure 3.1, the framework of operation research components can be described as follows:

1. Reality Problem Situation

   Reality consists of all aspects of the real world that concern with the problem situation. Reality provides all the data and initial inputs to the operations. A problem that occurs in the "real world problem" or "reality problem" that must be faced and resolved.

2. Conceptual Model

   After real poblem formulation, the arrow or path circle labelled "Conceptual Model" is meant to indicate that the "first phase" of the solving will be formulated into a conceptual model of the problem situation

3. Scientific Model

   After a conceptual model has been formed, scientific model can be formed. The purpose of scientific model is to provide solutions in solving the problem.

4. Solution

   This step discusses the results of the scientific model that solves some of the problems encountered in the real world or real problem. This solution is the basis for recommendations and advice to the decision maker.

Mitroff and Sagasti,(1973) stated that there are four phases in viewing system or process problem solving as illustrated in figure 3.1, there is an arrow leading to second phase which is a great conceptual model and the solution.This is the process of the feedback from solution to a great conceptual model. It is also can be defined as the verification process to test a relevance of an obtained solution by comparing early concept from situation problem. Test validation aims to test consistency internal model, including in phase unified. The relation between model scientific and solutions can reasonably properly called with model solving. Last, implementation of solution may be regarded as relations connecting solution to reality.

3.2 Reality Problem Situation and Company Profile

This research was conducted as a real case research in the industry. The data were collected from CV. Huda Karya. CV. Huda Karya is a cast iron industry that has established since 15 September 1992 thaat located in Ceper, Klaten, Indonesia. Currently, CV. Huda Karya has 58 employees. This industry is designed to manufacture engine components with cast iron materials, such as screw, milling the inner cylinder, pulleys and other. CV Huda Karya tries to produce the high quality products, sustain, maintain customer confidence and consider the customer satisfaction. In order to maintain these goals, the industry needs to control the production process to meet the expected products' quality and quantity in accordance with the industry's target. In accordance with this problem, CV Huda Karya has emphasized to implement inventory management system to fulfil the customer needs. Inventory management is always related to inventory replenishment. CV Huda karya explains the problems faced regarding inventory are as follows:

1. Difficulties in determining the production quantity that could result in a product's shortage or excess due to business fluctuations.

2. There is no accurate technique to predict the production quantity, thereby the results could cause the prediction error that also affect the business performance.

In this case, determination of production quantity that will affect the business performance includes costs, determination of purchasing material, storage and time planning of production processes. For example, the costs become an important evaluation of the business performance. If poor decision happens in inventory replenishment, then higher expenses will emerged that cover procuring material, holding the material, produce the product and product’s delivery. Otherwise, a good production planning provides sufficient availability of raw material at low costs. In the planning and inventory control, it first needs to monitor the overall inventory within industry. After that, to conduct inventory replenishment, needs to consider effective decision-making based on historical data. Past information about production quantity can be used to help predict the industry’s plan for the next production. Therefore, in order to overcome the inventory problems in the industry, this research proposes the model prediction for quantity production. This model can beneficial to the production manager in determining effective decision for production quantity. Thereby, production manager can also manage the flow of material from beginning process and the final process delivery.

3.3 Conceptual Model

In this stage, the the level of the organizational relationship give essential information in building a a great conceptual model as shown in the figure 3.2.

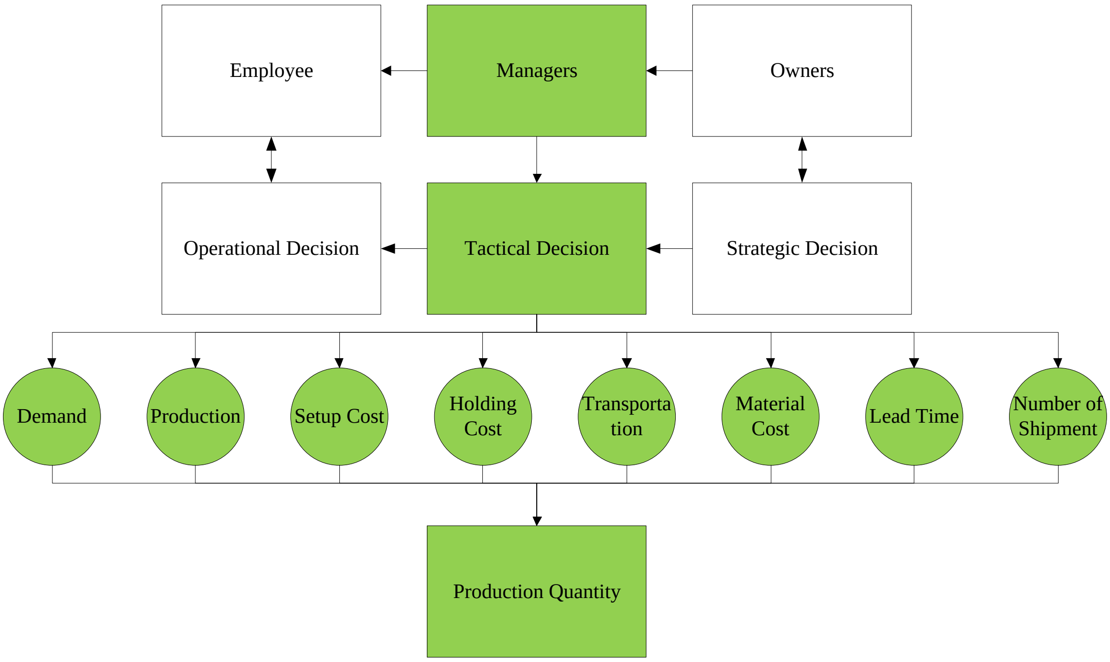

Figure 3.2 Conceptual Model

This research focus on tactical decision. Based on the problem of inventory replenishment, a production manager who will determine the decision of Production Quantity (PQ). From real industry, several variables that affect the decision making of PQ has been investigated such as demand, material cost, setup cost, holding cost, production and transportation cost, lead time and number of shipment. In this context, the development of prediction models on production quantity in the form of costs and amount of each month. Good decision that resulted from the process prediction is expected to have an impact on production process, so that it can minimize inventory cost.

3.4 Scientific Model

This stage discusses about designing a model for the production quantity prediction that can be used to make effective tactical decision. In this research, artificial neural network algorithm and support vector machine are used for production quantity determining. The step of developing the model can be seen in figure 3.3:

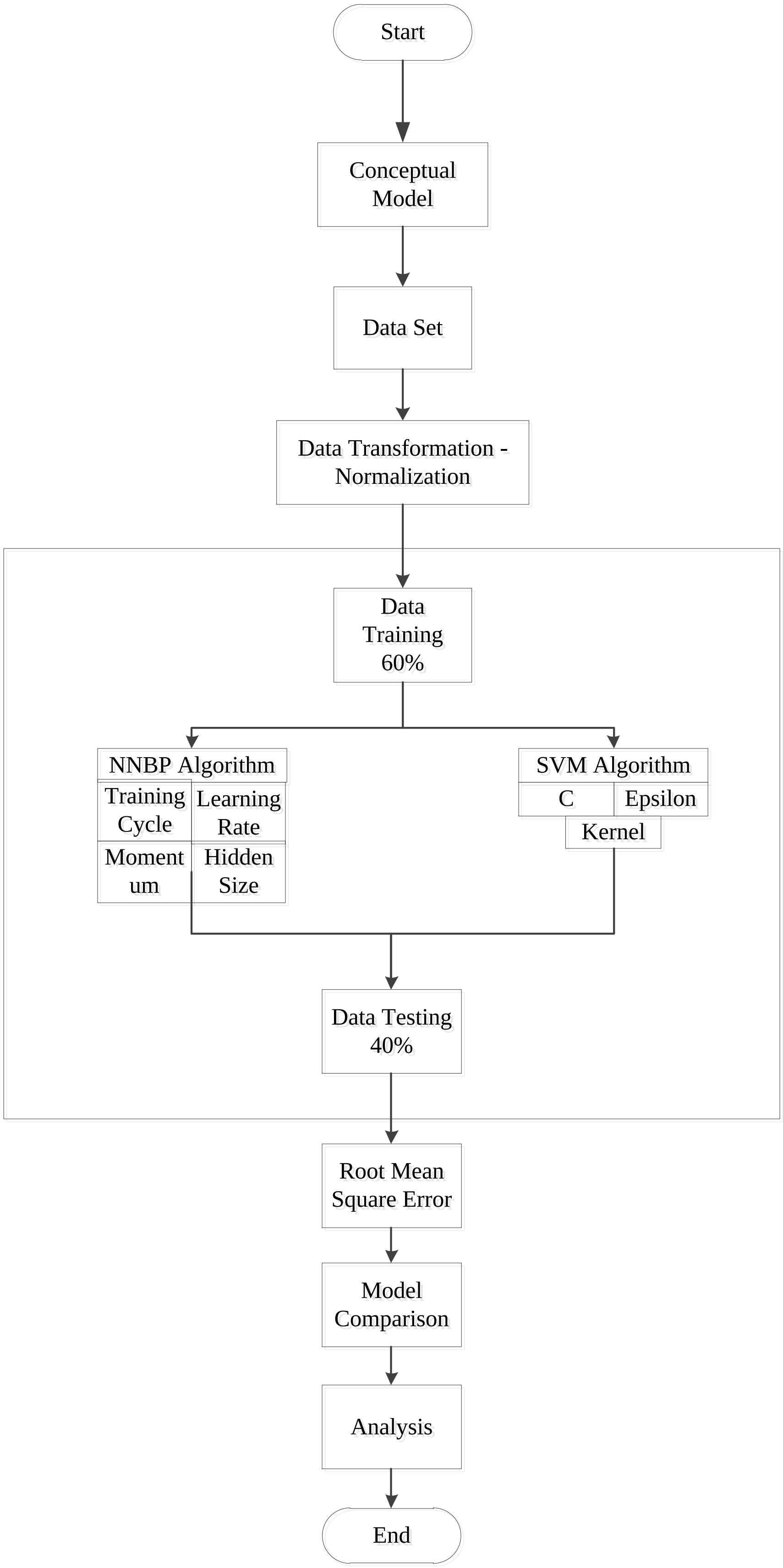

Figure 3.3 Model Development

The research is addressed to investigate the learning methods for the best prediction numbers of production. The model proposed in this research is artificial neural network algorithm that supported by vector machine algorithm, which is shown in figure3.3. For learning process of model ANN and SVM, data are split into two parts: training data 60% and testing data 40%. RMSE is used as the prediction on performance evaluation as accuracy indicator. Researcher uses a trial and error to get the minimum error in this procedure. In order to conduct the experiment, Rapid Miner software is used to develop the model.

The architecture of ANN is constructed by using feed forward neural network with one hidden layer. Learning process in ANN that used is back- propagation algorithm. In order to get optimal solution, back propagation algorithm need variation to maintain a momentum and a learning rate. SVR (SVM for Regression) is used for learning process in SVM. To obtain the performance, parameters C, epsilon and kernel are selected in SVR.

3.4.1 Data Requirement

The dataset is retrieved from a private company (manufacturing foundry in klaten, Indonesia). This dataset is the data history stored by the company. They are obtained by interviewing the owner of the company. There are 94 data collected (2006 to 2013) which includes:

$$\begin{bmatrix} X_i = \begin{bmatrix} Demand, D \\ Material\ Cost, M \\ Production, P \\ Setup\ Cost, S \\ Holding\ Cost, H \\ Transportation\ Cost, T \\ Lead\ Time, L \\ Number\ of\ Shipment, N \end{bmatrix}, & Y_i = [Production\ Quantity, Q] \end{bmatrix} \tag{3.1}$$

X_i = *input attribute* Y_i = *output*

This data is collected from a single product of grinding roll n70. Grinding Roll is the rice milling machine spare part used for peeling paddy to rice.

3.4.2 Data Transformation

Data preprocessing is used to transform the data before developing the models. In this research, data transformation technique is employed. Data transformation needs to be done in order to solve unbalanced data by converting the data, so that it can be used in learning artificial neural network algorithm. Normalization of input values for each measured attribute in the training will help speed up the learning stage. Data normalization is used to equalize the data among the attributes in order to obtain equal weight in the calculation of each attribute. According to Tian et al, (2010) formulation to normalize the data is as follows:

$$x_k = \frac{x - x_{min}}{x_{max - x_{min}}} \tag{0.2}$$

3.4.3 Neural Network Back Propagation Model

ANN is a learning system that supervised against receipt of information that is evidence of artificial neural network performance on human beings. Implementation in the NN is conducted by using a computer program to complete a number of calculation process. ANN is used for pattern recognition. Pattern recognition in ANN is an important component in the process of imitation on the human system function. One method of training is a supervised training (supervised learning). In supervised training, number of inputs and targets that serve to train the network are required to obtain the desired weight. NNBP is a supervised learning method that used to this research. This research proposes Neural Network Back propagation (NNBP) to develop models for production quantity prediction. The steps for developing NNBP model are as follows:

(Step1): Designing NNBP architecture as shown in figure 3.5

The architecture of NNBP model consists of six inputs, one output and one hidden layer. For number of hidden layer determination, trial and error experiment is applied.

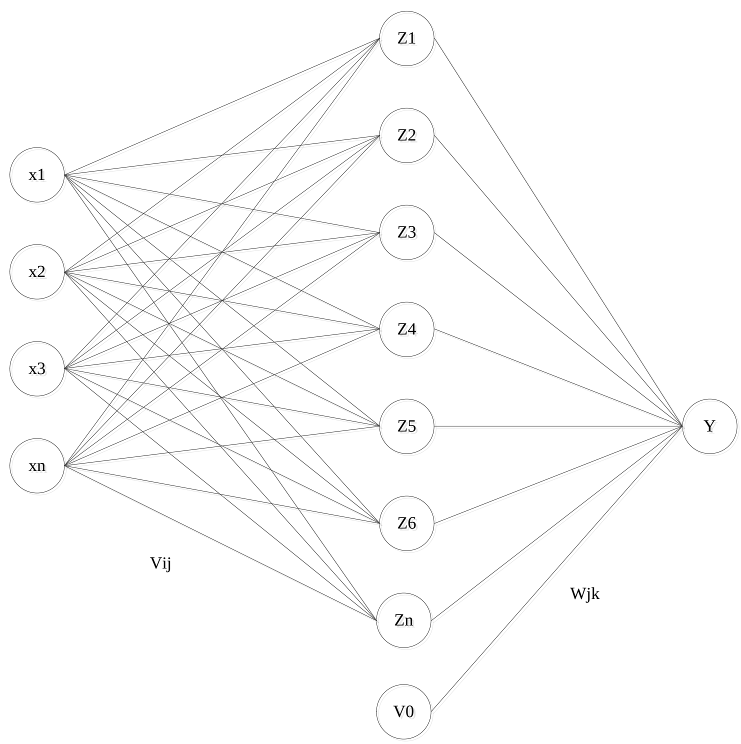

Figure 3.5 Architecture of Neural Network Back Propagation Model

From the figure 3.5, it can be seen the value of Xn where n is 1, 2, 3, 4, 5, 6, 7, 8 as input, while Zn is the number of hidden layer to be determined in this research and Yn is the output. The information can be seen as follows:

Annotation:

$X1$ = Demand (unit/month) X7 = Lead Times

$X2$ = Production (unit/month) X8 = Number of Shipment

$X3$ = Material Cost (Rp/unit) Zn = Number hidden layer n

$X4$ = Setup Cost (Rp/Setup) Yn = Production Quantity (unit) / shipment

$X5$ = Holding Cost (Rp/unit/month)

$X6$ = Transportation Cost

(Vij, i = 1…6, j = 1 … . . . n) is the value of the weights on the input i and neuron j in the hidden layer. (Wjk, j = 1…….n, k = 1) is the weight the neuron j and output k is the output results of prediction.

(Step 2): Initializing weights

The value of weights on Artificial Neural Network (ANN) is given by random values or small random values.

(Step3): As each pair of elements has experienced the learning process, it will be proceed to the next steps.

(Step4): Each unit of input (X_i, i=1,2,…,n) receives the signals and forwards the signal Xi to all units in an existing layer (hidden layers).

(Step5): Each unit on a hidden layer (Zj, j=1,2,…,p) summing the weighted input signals, use the activation function to compute the output signal and send the signal to all units in the layer above (output units).

(Step 6): Each unit of output Y_k (k=1,2,…,m) summing the weighted input signals, use the activation function to compute the output signal and send the signal to all units in the layer above (output units).

(Step 7): Calculating RMSE.

The error value is calculated using the Root Mean Square Error method (RMSE). RMSE is used to calculate the average error between the desired outputs in the training data with the output generated by the network. Below equation is used to check the stopping condition of the Root Mean Square Error:

$$RMSE = \sqrt{\frac{\sum\left(y_1 - y\_in_{k_k}\right)^2}{n}} \tag{3.3}$$

A period of time (epoch) is a set round of training phase. In this algorithm, weights are repaired after each training pattern is included. Once training is complete, then weight are saved.

3.4.4 Support Vector Machine Model

Support Vector Machines (SVM) is the technique of classification and regression, which is a non-linear algorithm development and was developed in Russia in the sixties. As has been outlined, the SVM can be used both for classification or regression, which limits the attention for the remainder of this work. The theory behind the use of SVM for estimation functions, introduced at the same time the most relevant terms and parameters, with attention to specific parameters. SVM has expanded to complete the estimation of nonlinear regression, regression SVM called for (SVR).

3.4.5 Support Vector Regression

The SVR is the application of the support vector machine (SVM) in terms of regression. In the case of regression output either a real number or continue. SVR is a method that can overcome the overfitting, so it will produce a great performance (Smola and Scholkopf, 2004).

There is a data set of training, λ (xj, yj) where j = 1,2, ... λ input with x = {x 1, x 2, x 3} ...∈ Rn and the corresponding output is y = {..., ..., yλ} ∈ r. SVR, will found a function f (x) has the greatest deviation from the actual target yi ε for all training data. The SVR, if ε equal to 0 will get a perfect regression.

For example we have the following function as a regression line

$$f(x) = w^T \varphi(x) + b \tag{3.4}$$

where φ (x) indicates a point in the feature space F x mapping results in the input space. W and b coefficients being estimated by means of minimizing risk functions (risk function) defined

$$min \frac{1}{2} \|w\|^2 + C \frac{1}{\lambda} \sum_{i=1}^{\lambda} L_{\epsilon}\big(y_i, f(x_i)\big) \tag{3.5}$$

Subject to

$$y_i - w\varphi(x_i) - b \le \varepsilon \tag{3.6}$$

$$w\varphi(x_i) - y_i + b \le \varepsilon, i = 1,2, \dots, \lambda \tag{3.7}$$

Where

$$L_{\varepsilon}\big(y_i, f(x_i)\big) = \begin{cases} |y_i - f(x_i)| - \varepsilon |y_i - f(x_i)| \geq 0 \\ 0, others \end{cases} \tag{3.8}$$

Factor $||w||^2$ is named as reguralisasi. Minimized $||w||^2$ is going to make a function as thin as possible, so that it can control the capacity of the function. The second factor in the function's purpose is the empirical error as measured by the ε-insensitive loss function. Using the idea of ε-insensitive loss function should be to minimize the norm of w in order to get a good generalization for a function regression f. Because it needs to complete the following optimization problem:

$$min \frac{1}{2} ||w||^2 \tag{3.9}$$

Subject to

$$y_i - w\varphi(x_i) - b \leq \varepsilon \tag{3.10}$$

$$w\varphi(x_i) - y_i + b \leq \varepsilon, i = 1,2, \dots, \lambda \tag{3.11}$$

$$\sum e^2 = \sum (y - \hat{y})^2 \tag{3.12}$$

$$= \sum \big(y - (b_0 + b_1 x)\big)^2$$

Assume that there is a function f which can approximate all the points (xi, yi) with precision ε. In this case, it is assumed that all points are in the range of f ± ε (feasible). In terms of impropriety (infeasible), where there may be some points that might be out of range of f ± ε, can be added to the variable ξ, ξ * slack to address delimiters are not feasible (infeasible constraints) in the optimization problem. Furthermore the above optimization problem can be formulated as follows:

$$min\frac{1}{2}\|w\|^2 + C\frac{1}{\lambda}\sum_{i=1}^{\lambda}(\xi_i, \xi_i^*) \tag{3.13}$$

Subject to

$$y_i - w^T\varphi(x_i) - b - \xi_i \leq \in, i = 1,2, \dots, \lambda \tag{3.14}$$

$$w\varphi(x_i) - y_i + b - \xi_i \leq \in, i = 1,2, \dots, \lambda \tag{3.15}$$

$$\xi_i, \xi_i^* \geq 0 \tag{3.16}$$

The constant C > 0 determines that the bargaining (trade off) between thinness function f and the upper limit of ε deviation still tolerated. All the deviation that greater than ε are pinalty of c. in SVR, ε is equivalent to the accuracy of the approximation to the training data. The value of ε small associated with high scores on the variable$\xi_i^*$and the accuracy of the approximation. On the contrary, a high value for ε that associated with the valueξ_i^*approximations are small and low. According to equation (5) high value for variable slack will cause mistakes on the empirical influence of regulatory factors. In the SVR, support vector training data is located at and outside the limits of the function f of decision, therefore the amount of support vector decreases with the rising ε.

In a dual formulation, problem optimization of SVR is as follows:

$$max - \frac{1}{2}\sum_{i-1}^{\lambda}\sum_{j=1}^{\lambda}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K\langle x_i - x_j\rangle \tag{3.17}$$

$$\sum_{i=1}^{\lambda}(\alpha_i - \alpha_i^*)y_i - \in \sum_{i=1}^{\lambda}(\alpha_i - \alpha_i^*) \tag{3.18}$$

Subject to

$$\sum_{i=1}^{\lambda}(\alpha_i - \alpha_i^*) = 0 \tag{3.19}$$

$$0 \le \alpha_i \le C, i = 1,2,\ldots,\lambda \tag{3.20}$$

Where C is defined by the user, K (xi, xj) is a dot-product of the kernel which is defined as $\mathrm{K(xi, xj)} = \varphi^T(x_i)\varphi^T(x_j)$ using langrange multiplier and optimal condition of regression function. Explicitly, it is formulated as follows:

$$f(x) = \sum_{i=1}^{\lambda}(\alpha_i - \alpha_i^*)\, K(x_i, x) + b \tag{3.21}$$

3.5 Solution

This stage is the resulted from the scientific model that will generate solutions. Scientific models investigate the learning methods for the best prediction numbers of production. The model proposed in this research is to compare the model of Artificial Neural Network and Support Vector Machine.

3.5.1 Research Tools

RapidMiner® software is used as a tool to process the data. Research tool is utilized for supporting the experimental design presented in this research. Research tool consists of hardware and software requirement.

Table 3.1 Specifications hardware and software

Software	Hardware
Operation System: Windows 8.1	CPU: Intel Core 2 Duo
Application: RapidMiner 5.2	Memory: 4GB
	Harddisk: 500GB

3.5.2 Performance Measurement

Several things turn to be next questions related to the prediction results whether the results of these predictions are accurate and generate optimal prediction models. There are several methods designated to answer above question, to measure the performance of the results in the form of an error calculation prediction. It is designated to measure on how well the network can learn so it will be easily recognized when compared with the new pattern. Network output error represents the difference between actual output and the target. The most common error function used in artificial neural network error function is the mean square (MSE). This error is used to decide when to stop the training process of artificial neural network. MSE function is defined as below:

$$Mean\ Square\ Error = \frac{\sum(actual - prediction)^2}{n} \qquad (3.22)$$

Mean Square Error is the sum of squared errors or the difference between the actual value (actual) and the predicted value, that number then divided by the amount of time, the data prediction that included to simplify the derivative expression are calculated in back propagation algorithm. To discover how close the approximation to the actual value, the measures that commonly used is root mean square error (RMSE) as follow:

$$Root\ Mean\ Square\ Error = \sqrt{\frac{\sum(actual - prediction)^2}{n}} \qquad (3.23)$$

Where n is the total value of the observation.

RMSE is the sum of squared errors or the difference between the actual and the predicted value then divides that number by the amount of time and data prediction then pull the square roots.

3.5.3 Evaluation and Validation

The model proposed for Production Quantity prediction is Neural Network Back Propagation (NNBP) and Support Vector Machine (SVM). First, the application of NNBP is employed to determine training cycle. Once the smallest RMSE is obtained, the training cycle value will be used to find the smallest RMSE on the learning rate and momentum. As the smallest RMSE of the training cycle is founded, learning rate and momentum then will be used to determine the neuron size in the hidden layer.

While the application of support vector machine performed similar steps in previous studies. Once the smallest RMSE is obtained, the paramater of C and epsilon value will be used to find the smallest RMSE. As the smallest RMSE ofNNBP and SVM is founded, it can solve the problem.

3.5.4 Comparison of Proposed Model

This comparison is performed to obtain a statistically significant difference in order to compare two or more algorithms. The difference of an algorithm depends on how well the inductive bias that matches the problem will behave differently on datasets, and the value of this error on data sets, can not be said to be normally distributed around some average accuracy. This means it is necessary to use a nonparametric test. Thus this comparison can use the t-test.

Evaluation and validation of model effectiveness is performed using Statistical technique t-Test (Paired Two Sample for Means) by comparing the average prediction accuracy of production quantity based on the average of RMSE. Statistical technique t-Test (Paired Two Sample for Means) is significant testing for the ρ value. The probability of obtainingt statistic test at least as extreme as the one that was actually observed, assuming that the null hypothesis is true. One often "rejects the null hypothesis" when ρ value is less than the predetermined significant level (α), indicating that the observed result would be highly unlikely under the null hypothesis. The statistical significance level (α) is 0.05. It means that no statistically significant difference if ρ value >0.05.

3.6 Summary

This chapter explains measures in the research consists of four main phases, those are: Reality Problem and Company Profile, Conceptual model, scientific model, and Solution. The first stage is the problems formulation that occurs in the industry that later will be solved. The second stage is a model construction to describe the problems and other factors that may influence the industry. Whereas, the third stage a solution formulation to solve the problem. Finally, the fourth stage that contains a solution that will be achieved and considered for decision making . Thus, in this research will generate a model prediction on Artificial Neural Network and Support Vector Machine with the aim to predict production quantity. For further, a model that eventually adopted will be implemented.

CHAPTER IV

EXPERIMENT RESULT

This chapter presented the experimentation and testing methods were used to develop artificial neural network and support vector machine.

4.1 Experimentation Result and Testing Methods

4.1.1 Neural Network Back Propagation Model (NNBP Model)

Artificial neural network algorithms are algorithms for supervised training and design for operation on a feed forward multilayer. Artificial neural network algorithms can be desribed when input training patterns is contributed to the network, then the pattern go to units on hidden layers to be forwarded to the outermost layer units.

Experimentation to estimate the amount of production was done by artificial neural networks. The predictive results are determined by the smallest RMSE. The data set will be divided into training and data. Research on the determination of production quantity prediction using the artificial neural network algorithm with software RapidMiner is described as follows:

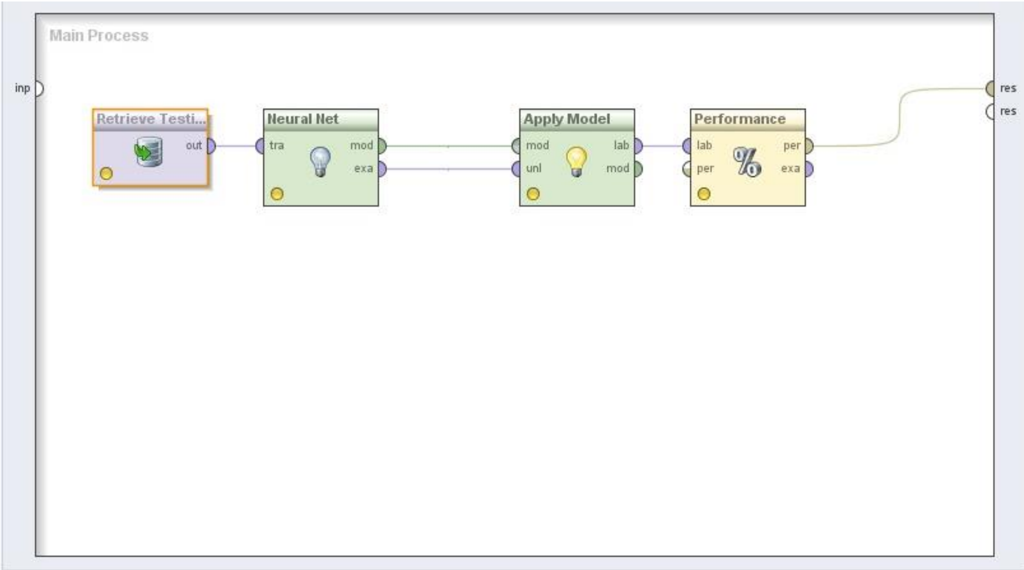

Figure 4.1 Training Model of ANN

To create NNBP model, trial and error will be used to get parameters of the model. Hence, there are several stages have to be fulfilled. The first stage is the determination of the value of training cycles that conducted by inserting test values with a range of 50 to 1000 for training cycles, and the value of 0.3 to 0.2 for the learning rate and momentum. Here are the results of the experiments that have been conducted to determine the value of training cycles:

Table 4.1 Determination of Training Cycle NNBP Model

Training Cycle	Learning Rate	Momentum	Hidden Nodes	Training RMSE
50	0.3	0.2	-1	0.037
100	0.3	0.2	-1	0.035
150	0.3	0.2	-1	0.034
200	0.3	0.2	-1	0.033
250	0.3	0.2	-1	0.031
300	0.3	0.2	-1	0.030
350	0.3	0.2	-1	0.029
400	0.3	0.2	-1	0.028
450	0.3	0.2	-1	0.027
500	0.3	0.2	-1	0.026
550	0.3	0.2	-1	0.025
600	0.3	0.2	-1	0.024
650	0.3	0.2	-1	0.024

Training Cycle	Learning Rate	Momentum	Hidden Nodes	Training RMSE
700	0.3	0.2	-1	0.023
750	0.3	0.2	-1	0.022
800	0.3	0.2	-1	0.021
850	0.3	0.2	-1	0.020
900	0.3	0.2	-1	0.019
950	0.3	0.2	-1	0.018
1000	0.3	0.2	-1	0.017

Value of training cycles are selected based on the smallest generated RMSE values. Based on the results of the above experiment, training cycles value is 1000. Values of 1000 are used for experiments in determining the value of learning rate. Learning rate value is determined by means of the trial and covers the value within range of 0.1 to 1. Value of training cycles were selected from previous experiments which is 1000, while the value of 0.2 is used for momentum. Here are the results of the experiments that have been conducted to determine the value of learning rate:

Table 4.2 Determination of Learning Rate NNBP Model

Training Cycle	Learning Rate	Momentum	Hidden Nodes	Training RMSE
1000	0.1	0.2	-1	0.028
1000	0.2	0.2	-1	0.026
1000	0.3	0.2	-1	0.017
1000	0.4	0.2	-1	0.015
1000	0.5	0.2	-1	0.010
1000	0.6	0.2	-1	0.009
1000	0.7	0.2	-1	0.072
1000	0.8	0.2	-1	0.037
1000	0.9	0.2	-1	0.028
1000	1.0	0.2	-1	0.026

The values of learning rate are selected based on the lowest RMSE values. Based on the above experimental results, the value of learning rate is 0.6. Value of 0.6 is used for experiments in determining the value of momentum. Value of the momentum is determined by carrying out the trials that includes the value within a range of 0 to 0.9.

Value of 1000 indicates cycles of training and learning rate 0.6 were selected based on previous experiments. Here are the results of the experiments that have been conducted to determine the value of the momentum:

Table 4.3 Determination of Momentum NNBP Model

Training Cycle	Learning Rate	Momentum	Hidden Nodes	Training RMSE
1000	0.6	0.0	-1	0.011
1000	0.6	0.1	-1	0.009
1000	0.6	0.2	-1	0.009
1000	0.6	0.3	-1	0.015
1000	0.6	0.4	-1	0.044
1000	0.6	0.5	-1	0.263
1000	0.6	0.6	-1	0.036
1000	0.6	0.7	-1	0.242

Based on the above experimental results, the parameter of the neural network back propagation was selected for the value of 1000 for the training cycles, 0.6 for the learning rate and 0.2 for the momentum. The next step is to determine the number of hidden layer neurons and sizes to find the lowest RMSE value. In this research selected number of one hidden layer is used and experiments are conducted on neurons sizes within range of 1 to 30 sizes. Following Table 4.4 are the results of Hidden Neuron Size test:

Table 4.4 Determination of Hidden Neuron Size NNBP Model

Training Cycle	Learning Rate	Momentum	Hidden Nodes	Training RMSE
1000	0.6	0.2	1	0.108
1000	0.6	0.2	2	0.028
1000	0.6	0.2	3	0.014
1000	0.6	0.2	4	0.022
1000	0.6	0.2	5	0.035
1000	0.6	0.2	6	0.009
1000	0.6	0.2	7	0.033
1000	0.6	0.2	8	0.129
1000	0.6	0.2	9	0.007
1000	0.6	0.2	10	0.060
1000	0.6	0.2	11	0.014

Training Cycle	Learning Rate	Momentum	Hidden Nodes	Training RMSE
1000	0.6	0.2	12	0.050
1000	0.6	0.2	13	0.101
1000	0.6	0.2	14	0.041
1000	0.6	0.2	15	0.192
1000	0.6	0.2	16	0.198
1000	0.6	0.2	17	0.167
1000	0.6	0.2	18	0.173
1000	0.6	0.2	19	0.163
1000	0.6	0.2	20	0.194
1000	0.6	0.2	21	0.217
1000	0.6	0.2	22	0.183
1000	0.6	0.2	23	0.178
1000	0.6	0.2	24	0.254
1000	0.6	0.2	25	0.206
1000	0.6	0.2	26	0.168
1000	0.6	0.2	27	0.337
1000	0.6	0.2	28	0.214
1000	0.6	0.2	29	0.198
1000	0.6	0.2	30	0.251

Based on above experiment, the smallest RMSE values can be calculated using RapidMiner. Trial results by using a neural network back propagation model is retrieved in Table 4.4. The best parameter results of NNBP are illustrated in table 4.5:

Table 4.5 Parameter of Neural Network Back Propagation Model

Parameters Neural Network Back Propagation	
Training Cycle	1000
Learning Rate	0.6
Momentum	0.2
Hidden Neuron Size	9
RMSE	0.007

To determine model test, Neural Network Back Propagation algorithm is used in the framework of RapidMiner as follows:

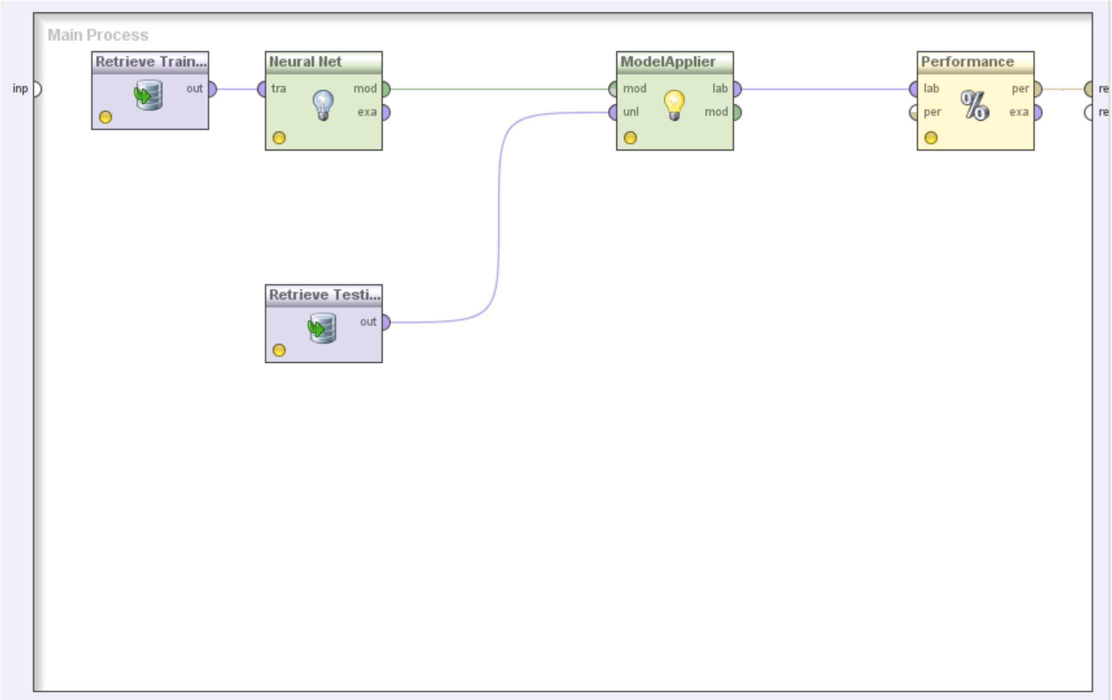

Figure 4.2 Testing Model of ANN

Based on the results of ANN parameters, the predicted results can be notified. Table 4.6 shows the results of prediction using the ANN method.

Table 4.6 Result Actual Vs Prediction NNBP Model

Production Quantity Prediction		
Data Set	**Actual**	**Prediction Neural Netwok**
1	28	28
2	28	28
3	28	28
4	26	26
5	25	28
6	26	26
7	25	25
8	23	23
9	23	23
10	23	23
11	28	28
12	26	26
13	25	24
14	28	28
15	28	28
16	26	26

Production Quantity Prediction		
Data Set	**Actual**	**Prediction Neural Netwok**
17	28	28
18	26	26
19	22	22
20	25	26
21	25	25
22	23	23
23	25	25
24	23	23
25	28	28
26	26	26
27	25	25
28	23	23
29	22	22
30	21	22
31	23	23
32	25	25
33	23	23
34	25	25
35	26	26
36	25	25
37	23	23
38	22	21
39	25	25
40	23	23
41	21	22
42	25	25
43	26	26
44	26	26
45	28	28
46	28	28
47	26	26
48	28	28
49	28	28
50	28	28
51	26	26
52	26	26
53	26	26

Production Quantity Prediction		
Data Set	**Actual**	**Prediction Neural Netwok**
54	28	28
55	28	28
56	28	28
57	26	26
58	25	25
59	26	26
60	28	28
61	26	26
62	28	28
63	26	26
64	26	26
65	25	25
66	25	25
67	28	28
68	28	28
69	28	28
70	26	26
71	28	28
72	28	28
73	26	26
74	26	26
75	28	28
76	28	28
77	26	26
78	25	25
79	28	28
80	28	28
81	28	28
82	26	26
83	26	26
84	25	25
85	28	28
86	26	26
87	28	28
88	28	28
89	26	26
90	28	28

Production Quantity Prediction		
Data Set	**Actual**	**Prediction Neural Netwok**
91	28	28
92	26	26
93	28	28
94	28	28

4.1.2 Support Vector Machine Model (SVM Model)

Support vector machine is a supervised learning methods used for classification and regression. SVM has been developed for pattern recognition problems. SVM tries to identify a hyperplane, which serve as separators for data classification, in a multi-dimensional space. It has expanded to solve nonlinear regression estimation, and shows excellent performance.

Experimentation to estimate the amount of production was done by support vector machines. The predictive results are determined by the smallest RMSE. The data set will be divided into training and data testing. Research on the determination of production quantity prediction using support vector machine algorithm using software RapidMiner is described as follows:

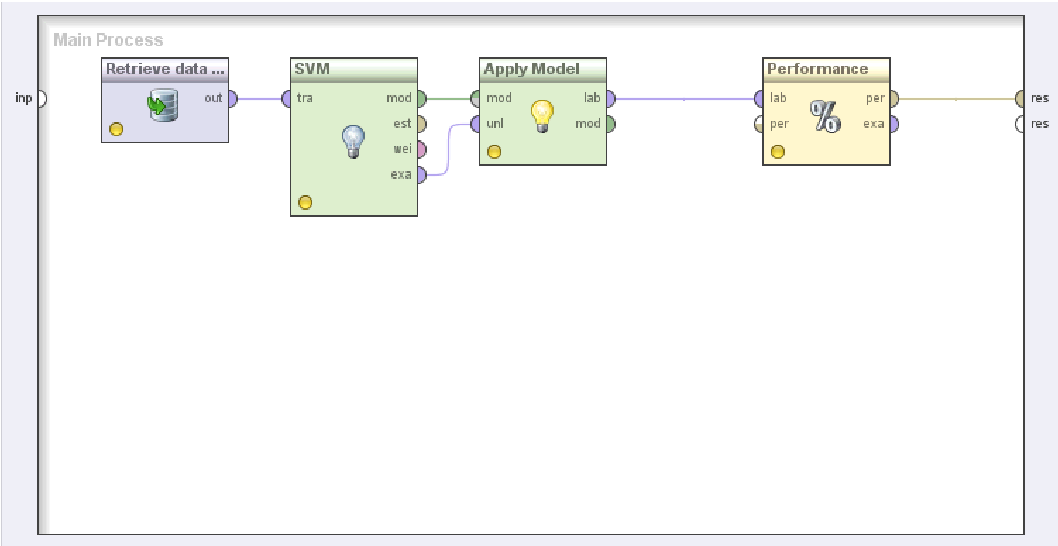

Figure 4.3 Training Model of SVM

To create SVM model, trial and error will be used to get parameters of the model. SVM Model construction is determined by entering test C, epsilon and dot kernel. In this research, there are several stages have to be accomplished for building SVM Model. The first stage is the determination of the value of C that established by experimenting values within range of 0 to 1, and a value of 0 for the epsilon. Following are the results from the experiments that have been conducted:

Table 4.7 Determination of C SVM Model

C	Epsilon	Training RMSE
0	0	0.499
0.1	0	0.299
0.2	0	0.545
0.3	0	0.749
0.4	0	0.966
0.5	0	1.211
0.6	0	1.470
0.7	0	1.725
0.8	0	2.005
0.9	0	2.279
1	0	2.554

The value of C is chosen based on the smallest value of RMSE result. It is concluded that value of C is 0.1. The value of the next 0.1 will be used for experiments in determining epsilon. By Specifying the value of epsilon with the attempt of, inserting a value within range of 0-1. Following are the results from the experiments that have been conducted to determine the value of epsilon:

Table 4.8 Determination of Epsilon SVM Model

C	Epsilon	Training RMSE
0,1	0	0.299
0,1	0,1	0.159
0,1	0,2	0.171
0,1	0,3	0.377
0,1	0,4	0.330
0,1	0,5	0.299

C	Epsilon	Training RMSE
0,1	0,6	0.299
0,1	0,7	0.299
0,1	0,8	0.299
0,1	0,9	0.299
0,1	1	0.299

Based on above experiment, trial results obtained by using vector support machine model are presented in table 4.8. The best results parameter of SVM are illustrated in Table 4.9:

Table 4.9 Parameter of SVM Model

Parameters SVM	
C	0.1
Epsilon	0.1
RMSE	0.159

To determine the model test, Support Vector Machine algorithm in the framework RapidMiner is used as follows:

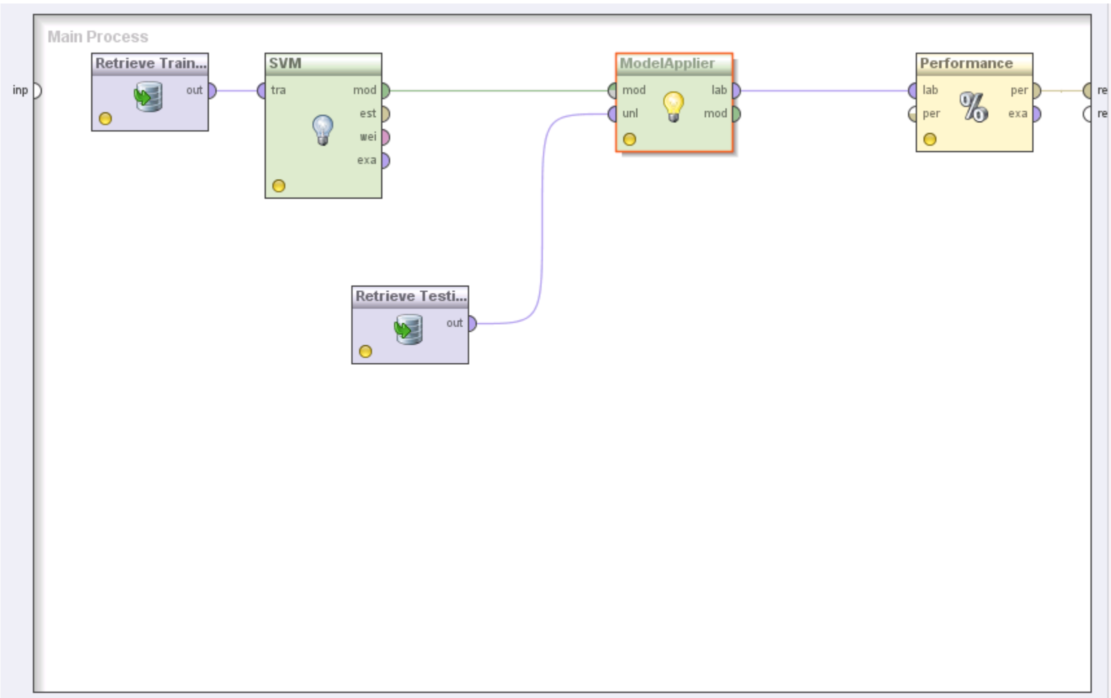

Figure 4.4 Testing Model of SVM

Based on the results of SVM parameters, the predicted results can be notified. Table 4.10 shows the results of prediction using the SVM method.

Table 4.10 Result Actual Vs Prediction SVM model

Production Quantity Prediction		
Data Set	**Actual**	**Prediction SVM**
1	28	26
2	28	25
3	28	26
4	26	25
5	25	25
6	26	25
7	25	25
8	23	25
9	23	26
10	23	25
11	28	24
12	26	25
13	25	26
14	28	26
15	28	26
16	26	25
17	28	25
18	26	25
19	22	25
20	25	25
21	25	25
22	23	26
23	25	25
24	23	25
25	28	26
26	26	26
27	25	25
28	23	26
29	22	25
30	21	26
31	23	25
32	25	25
33	23	25
34	25	26
35	26	26
36	25	25
37	23	26

Production Quantity Prediction		
Data Set	**Actual**	**Prediction SVM**
38	22	26
39	25	25
40	23	26
41	21	26
42	25	26
43	26	26
44	26	26
45	28	26
46	28	26
47	26	26
48	28	26
49	28	27
50	28	27
51	26	27
52	26	26
53	26	26
54	28	26
55	28	26
56	28	26
57	26	26
58	25	26
59	26	26
60	28	26
61	26	26
62	28	27
63	26	28
64	26	27
65	25	27
66	25	27
67	28	27
68	28	27
69	28	26
70	26	26
71	28	26
72	28	27
73	26	28
74	26	27
75	28	27

Production Quantity Prediction		
Data Set	**Actual**	**Prediction SVM**
76	28	27
77	26	27
78	25	27
79	28	27
80	28	27
81	28	27
82	26	27
83	26	27
84	25	27
85	28	28
86	26	28
87	28	27
88	28	27
89	26	27
90	28	27
91	28	28
92	26	27
93	28	27
94	28	27

Table 4.11 shows the result of data training and data testing on NNBP and SVM model based on performance evaluation RMSE as follows:

Table 4.11Result of RMSE NNBP and SVM model

Predictor	Training Data	Testing Data
NNBP	0.007	0.024
SVM	0.159	0.235

T-test will evaluated under statistical technique, which is t-Test (Paired Two Sample for Means) are conducted to compare between NNBP and SVM model. The result of t-test is presented as follows:

Table 4.12 T-Test RMSE on training NN and SVM model

Predictor	T-Test	Result
ANN and SVM	1.000	Not Sig. (ρ–value > α=0.05)

4.2 Summary

This chapter explained the step by step of experimentation on Neural Network Back Propagation and Support Vector Machine. The experiment using Rapid Miner software. The data set will be divided into training and data testing. The predictive results is determined by the smallest RMSE.T-test is applied to evaluate the models. Next chapter will confer the discussion that implemented in this research.

CHAPTER V

DISCUSSION

This chapter will discuss about the result of analysis from the experimentation on artificial neural network and support vector machine model.

5.1 Neural Network Back Propagation Model

Results of the experiments have been performed to get the NNBP model. Trial and error process is used to determine the parameters of the NNBP model, while performance evaluation applies the RMSE to get lowest value in the training process by using the specified parameters. Based on the experiments that have been conducted in table 4.5, optimal NNBP model architecture for Production Quantity Prediction consists of 8 attributes in the input layer, one hidden layer with 9 neurons and one attributes of the output layer. The training process of RMSE resulted 0.007. Prediction result is revealed by using NNBP parameters with training cycle of 1000, learning rate of 0.6 and momentum is 0.2.

5.2 Support Vector Machine Model

Results of the experiments have been conducted to get the SVM model. Trial and error process is used to determine the parameters of the SVM model, while performance evaluation applies the RMSE to get lowest value in the training process by using the specified parameters. Based on the experiments that have been conducted in table 4.10, the results of experiments in determining parameter SVM C is 0.1 and epsilon is 0.1. By getting the best parameters, it can be concluded that the results of experiments using support vector machine method to get the smallest RMSE is 0.159.

5.3 Comparison of Proposed Model

Table 4.11 shows that NNBP model, in order to predict production quantity, has obtained the best RMSE value as 0.007 by conducting trial and error experiment.The t-test is used to ensure a significant different between these two models (NNBP and SVM). Comparison is based on hypothesis that, if ρ-values is more than the predetermined significant level (α), the result has no significant different. Otherwise, if ρ-values is less than predetermined significant level(α), the result has significant different. In this research, the significant difference level (α) will be determined to be 0.05. Based on the comparison result shown in table 4.12, gives ρ-values is 1.000. The result shows that all ρ-values still higher than significant level (α=0.05), it proves that comparison all proposed models have no significant differences.

5.4 Summary

This chapter describes the implementation of ANN and SVM model and the results of the experiment in generating predictions on production quantity. Two models have been designed to obtain accurate predictions that include Neural Network Back Propagation (NNBP) and Support Vector Machine (SVM). The models are experimented using Rapid Miner software.

CHAPTER VI

CONCLUSION AND SUGGESTION

This chapter presents conclusions of the research results, research contribution and suggestions for further research.

6.1 Conclusion

In order to solve this problem, to predict the quantity of production, l Artificial Neural Network and Support Vector Machine are employed. The data set will be divided into training data 60% and testing data 40%. Training data will be used to find the parameter values of ANN and the data testing will be used to determine whether the obtained parameters can process new data. The models were tested to obtain the smallest RMSE value of each algorithm. The test that conducted by using the neural network with the adjusted parameters on training cycle, learning rate, momentum and hidden size obtains 0,007 for RMSE value. While test by using a support vector machine with adjustments on the parameters of C, epsilon and RMSE values obtains 0.159. It can be concluded that the data testing using Artificial Neural Networks is better conducted than Support Vector Machine method when it is implemented in CV. Huda Karya.

The t-test is performed to measure the performance of the model. The comparison result of the two models based on t-test, it can be inferred that the ρ-value is 1.000. The results shows that there is no significant difference between the proposed models. It is due all ρ-values still higher than significant level (α) = 0.05. It is due to NNBP model still provides lower RMSE. Therefore, NNBP can successfully predict effective decision for production quantity. Based on the results, Artificial Neural Network (ANN) shows better performance rather than SVM for production quantity prediction.

6.2 Research Contribution

Based on the experimental result, this research also contributes to:

1. Practice
   a. Artificial neural network and Support Vector Machine model for production quantity prediction.
   b. This proposed prediction ANN and SVM model can help a manager to make effective decision-making based on historical data.
2. Knowledge

   This research can contribute to knowledge of ANN and SVM for prediction.

6.3 Suggestion

This research proves that the prediction model based on NNBP and SVM model can successfully implemented in determining effective decision making for production quantity under uncertainty factors. However, in order to increase the accuracy of the model, then some recommendations from this research can be further advised as follows:

1. This research on SVM model uses only one kernel parameter. Then, for further research it is suggested to use other kernel parameters as a comparison.

2. For further research, combining ANN and SVM model with other optimization method in order to improve ANN and SVM such as Genetic Algorithm, Particle Swarm optimization**.**

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APPENDIX

Data set of Production Quantity from CV. Huda Karya, Klaten, Indonesia

Demand (unit/month)	Production (unit/month)	Material Cost (Rp/unit)	Setup Cost (Rp/Setup)	Holding Cost (Rp/unit/month)	Transportation Cost	Lead Time (times/days/unit)	Number of shipment	Production Quantity (unit) / shipment
400	430	15000	40000	600	180000	15	1	28
250	250	15000	50000	600	180000	15	1	28
500	550	15000	35000	600	180000	15	2	28
600	630	15000	30000	600	180000	16	2	26
450	500	15000	50000	600	180000	17	2	25
400	440	15000	45000	600	180000	16	2	26
500	535	15000	55000	600	180000	17	1	25
350	400	15000	60000	600	180000	18	1	23
400	430	15000	45000	600	190000	18	1	23
500	550	15000	50000	600	190000	18	2	23
600	630	15000	55000	600	190000	15	2	28
500	530	15000	45000	600	190000	16	2	26
300	335	16000	35000	700	200000	17	1	25
400	440	16000	40000	700	200000	15	1	28
370	400	16000	50000	700	200000	15	1	28
500	520	16000	55000	700	200000	16	2	26
600	630	16000	60000	700	200000	15	2	28

Demand (unit/month)	Production (unit/month)	Material Cost (Rp/unit)	Setup Cost (Rp/Setup)	Holding Cost (Rp/unit/month)	Transportation Cost	Lead Time (times/days/unit)	Number of shipment	Production Quantity (unit) / shipment
700	720	16000	57000	700	200000	16	2	26
600	630	16000	65000	700	200000	19	2	22
450	470	16000	70000	700	200000	17	1	25
480	500	16000	50000	700	200000	17	1	25
500	520	16000	30000	700	200000	18	2	23
600	650	16000	45000	700	200000	17	2	25
750	800	16000	50000	700	200000	18	2	23
400	440	17000	40000	700	200000	15	1	28
450	460	17000	50000	700	200000	16	1	26
500	520	17000	55000	700	200000	17	1	25
450	460	17000	45000	700	210000	18	1	23
600	630	17500	60000	700	210000	19	2	22
540	550	17500	54000	700	210000	20	2	21
550	570	17500	65000	700	210000	18	2	23
600	620	17500	65000	700	210000	17	2	25
400	410	17500	70000	700	210000	18	2	23
370	380	18000	55000	700	210000	17	1	25
400	420	18000	65000	700	220000	16	2	26
600	620	18000	55000	700	220000	17	2	25
650	670	18500	45000	750	230000	18	2	23
460	500	18500	54000	750	230000	19	1	22
500	530	19000	65000	750	235000	17	2	25

Demand (unit/month)	Production (unit/month)	Material Cost (Rp/unit)	Setup Cost (Rp/Setup)	Holding Cost (Rp/unit/month)	Transportation Cost	Lead Time (times/days/unit)	Number of shipment	Production Quantity (unit) / shipment
600	630	19000	55000	750	235000	18	2	23
700	730	19000	45000	750	240000	20	2	21
500	520	19000	56000	750	240000	17	1	25
450	430	19000	55000	750	240000	16	1	26
500	520	19000	60000	750	240000	16	2	26
500	510	20000	56000	750	240000	15	1	28
600	630	20000	55000	750	250000	15	2	28
700	720	20000	45000	750	250000	16	2	26
350	400	20000	50000	750	250000	15	1	28
300	330	20000	35000	800	250000	15	1	28
250	300	20000	37000	800	250000	15	1	28
350	400	20000	40000	800	260000	16	1	26
500	530	20000	50000	800	260000	16	2	26
700	725	20500	45000	800	260000	16	2	26
350	380	20500	50000	800	265000	15	1	28
435	450	20500	47000	800	265000	15	1	28
600	630	20500	53000	800	270000	15	2	28
550	590	20500	55000	800	270000	16	1	26
600	630	20500	60000	800	270000	17	2	25
400	440	20500	65000	800	275000	16	2	26
500	530	20500	50000	800	275000	15	1	28
750	780	21000	45000	900	275000	16	2	26

Demand (unit/month)	Production (unit/month)	Material Cost (Rp/unit)	Setup Cost (Rp/Setup)	Holding Cost (Rp/unit/month)	Transportation Cost	Lead Time (times/days/unit)	Number of shipment	Production Quantity (unit) / shipment
700	720	21000	35000	900	280000	15	2	28
300	330	21000	38000	900	280000	16	1	26
400	440	21000	40000	900	280000	16	1	26
450	480	21000	45000	900	280000	17	1	25
600	630	22000	50000	900	280000	17	2	25
500	580	22000	47000	900	290000	15	1	28
450	470	22000	50000	900	290000	15	1	28
600	650	22000	60000	900	290000	15	2	28
620	640	22000	60000	900	290000	16	2	26
700	730	22000	50000	900	300000	15	2	28
600	620	22000	50000	900	300000	15	2	28
300	320	22000	40000	900	300000	16	1	26
400	450	22000	45000	900	300000	16	1	26
450	500	23500	50000	900	310000	15	2	28
370	390	23500	60000	900	310000	15	1	28
500	540	23500	65000	900	315000	16	2	26
400	420	23500	55000	1000	320000	17	1	25
385	400	23500	60000	1000	320000	15	1	28
370	400	23500	48000	1000	335000	15	1	28
400	450	24000	45000	1000	335000	15	1	28
600	640	24000	40000	1000	340000	16	2	26
500	530	24000	50000	1000	350000	16	1	26

Demand (unit/month)	Production (unit/month)	Material Cost (Rp/unit)	Setup Cost (Rp/Setup)	Holding Cost (Rp/unit/month)	Transportation Cost	Lead Time (times/days/unit)	Number of shipment	Production Quantity (unit) / shipment
570	600	24000	45000	1000	350000	17	2	25
550	570	25000	40000	1000	350000	15	2	28
400	410	25000	45000	1000	360000	16	1	26
625	640	26000	47000	1000	360000	15	2	28
600	650	26000	50000	1000	365000	15	2	28
500	520	26000	60000	1000	370000	16	1	26
520	560	27500	60000	1000	380000	15	2	28
550	600	27500	65000	1200	390000	15	2	28
700	720	28000	65000	1200	390000	16	2	26
650	680	28000	68000	1200	400000	15	2	28
500	530	28000	78000	1200	400000	15	1	28