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# EXPONENTIAL SMOOTHING FORECASTING TECHNIQUE: A CASE STUDY OF SOLID STATE DRIVE PRODUCTION

By
CANISORN AROONSWASDI

A Final Report of the Six-Credit Course
SCM 2202 Graduate Project

Submitted in Partial Fulfillment of the Requirements for the Degree of
MASTER OF SCIENCE IN SUPPLY CHAIN MANAGEMENT

Martin de Tours School of Management
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Examination Committee:

1. Asst. Prof. Brian Lawrence (Chair) ..........................
2. Dr. Piyawan Puttibarncharoensri (Member) ..........................
3. Dr. Adam Goh (Advisor) ..........................

Approved for Graduation on: March, 21, 2012

Martin de Tours School of Management
Assumption University
Bangkok, Thailand

March 2012

**Assumption University**
**Martin de Tours School of Management and Economics**
**Master of Science in Supply Chain Management**

**Declaration of Authorship Form**

I, Canisorn Aroonswasdi

declare that this thesis/project and the work presented in it are my own and has been generated by me as the result of my own original research.

Exponential Smoothing Forecasting Technique: A Case Study of Solid State Drive Production

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**Student Name:** Janisorn Iroonswasdi

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## ADVISOR'S STATEMENT

I confirm that this thesis/project has been carried out under my supervision and it represents the original work of the candidate.

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Date 8 April 12

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Canisorn Aroonswasdi

Assumption University

March 2012

# ABSTRACT

The purpose of this graduate project is to focus on developing a suitable forecasting model for a Solid State Drive (SSD) manufacturing company. There had been no systematic forecasting in this company; consequently, the company faced the situation of uncertain demand. Moreover, according to government policy, minimum wages will increase in the near future. The company needed an effective production plan in order to reduce overtime expense, while fulfilling customer demand, including sudden unexpected demand.

Time series forecasting techniques are applied in this case study. Simple exponential smoothing and double exponential smoothing techniques are developed and tested. The results show that the double exponential smoothing technique performs better than the simple exponential smoothing technique. The application of the double exponential smoothing technique provides a low percentage of forecast error, which indicates that the application can reduce demand variations. Consequently, it can identify cost saving for the company, in two categories, carrying cost and opportunity cost.

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Signed

( Asst. Prof. Brian Lawrence )

Contact Number / Email address blawrence@au.edu

Date:

# CHAPTER I

# GENERALITIES OF THE STUDY

## 1. Introduction

In today's dynamic business environment which demands innovation for competitive advantage, all firms must seek a practical approach to increase productivity, maximize profits and minimize operation costs, as their businesses are bottom-line driven in the context of changing needs and high customer satisfaction demand. In order to meet customer needs, adaptation is a very important issue for all firms. However, it will be a trade-off with the cost, which must positively relate with the level of customer satisfaction. Furthermore, external factors such as economic conditions, technology innovation, and political issues, also affect business. Therefore, a business firm must develop a strategy to deal with the uncontrollable factors that hinder the accomplishment of the firm's business goal.

Business uncertainty has a direct impact on firms, in matching supply and demand, and the variations between these two pose great challenges in the firm's decision-making process, in sales, production, procurement, and even investment. All business firms would like to know the expected demand from their customers in order to fulfill their customers' needs. Thus, using the right forecasting technique would help firms to predict or forecast customer demand.

With the rapid advent of software technology, many forecasting software tools and techniques, with effective formulas and algorithms, have been developed which are appropriate for different patterns of demand. However, the forecasting approach is unable to achieve one hundred percent accuracy and precise measurement due to inherent forecasting error. Therefore, the user has to assess current techniques of forecasting for model reliability and degree of accuracy. Accurate forecasting requires historical data for effective forecasting and the different characteristics of demand in each business type have an impact on the selection of a forecasting model.

## 1.1 Background of the Research

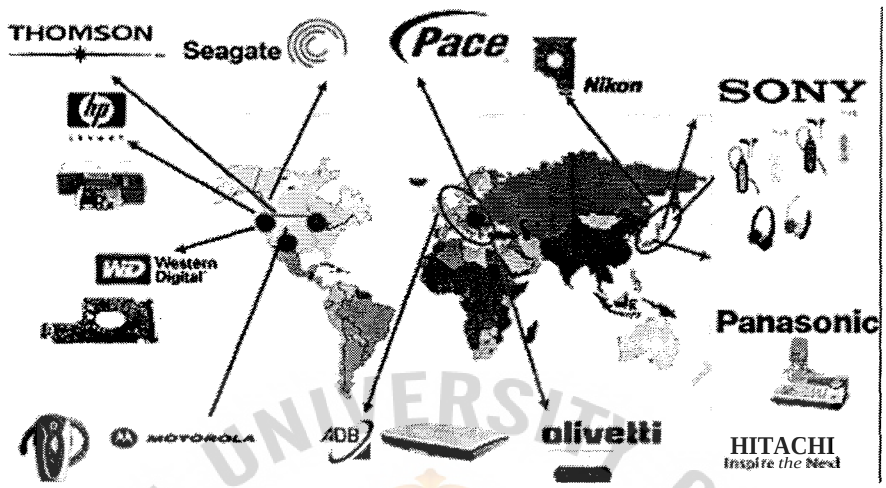
Company C is an Electronics Manufacturing Services (EMS) business. The company was founded with an initial capital of 125 million baht on 4 December 1989. At present, the company has a registered capital of 4,278 million Baht and paid up capital of 4,078 million Baht. The company employs 6,000 employees in Thailand, producing electronics products for major brands worldwide, such as Hewlett Packard, Western Digital, Seagate, Panasonic, Motorola, Hitachi, Pioneer, Advance Digital Broadcast and Nikon.

The company's core business is an Original Equipment Manufacturer (OEM). An OEM has the role of both Customer and Supplier of an EMS. It is a customer when it contracts the EMS to execute the manufacture and logistics of products, and a supplier when it delivers some of the strategic and main components of the final product, always maintaining confidentiality of the product design. It provides a one-stop turnkey and total solution services for clients, starting with Printed Circuit Board Assemblies (PCBA) using various placements and soldering technologies. The company's OEM products are categorized into three groups as follows;

1. Computing products: Ink-jet printers, multi-function printers, dot- matrix printers, Photo printers, and PCBA for hard disk, external hard disk drive and digital camera.
2. Telecommunication products: wireless phones, mobile phones for Bluetooth headsets and Set Top Boxes.
3. The other business units are equipment products, such as fax machines.

The company exports its products to major clients all over the world, as illustrated in Figure **1.1** below.

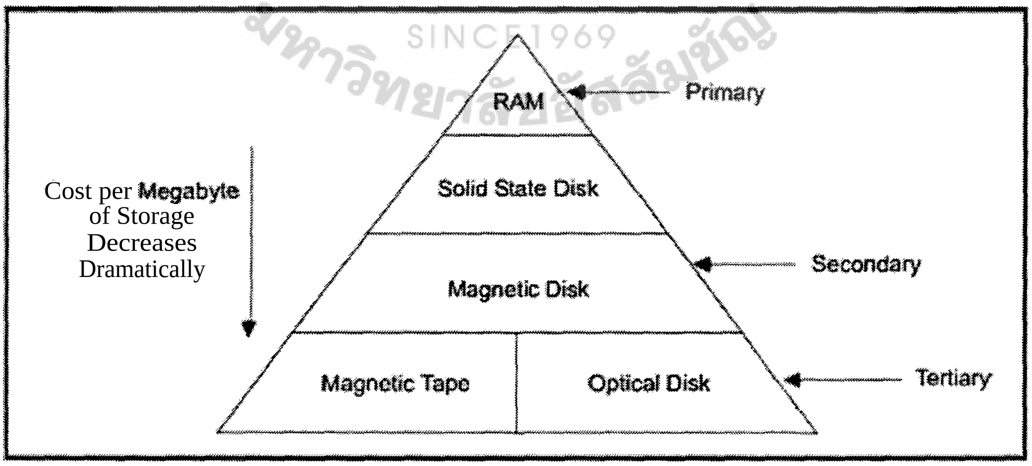
**Figure 1.1: Location of Countries to which OEM Exports**




Source: Compiled from company sales department

This case study is about one Electronics Manufacturing Service provider (EMS) in Thailand. One of its products is the Solid State Drive (SSD), which is a data storage device that uses solid-state memory to store persistent data. SSD emulates a hard disk drive interface in most applications, as an SSD using flash memory for storage data. The following Figure 1.2 illustrates the variety of data storage.

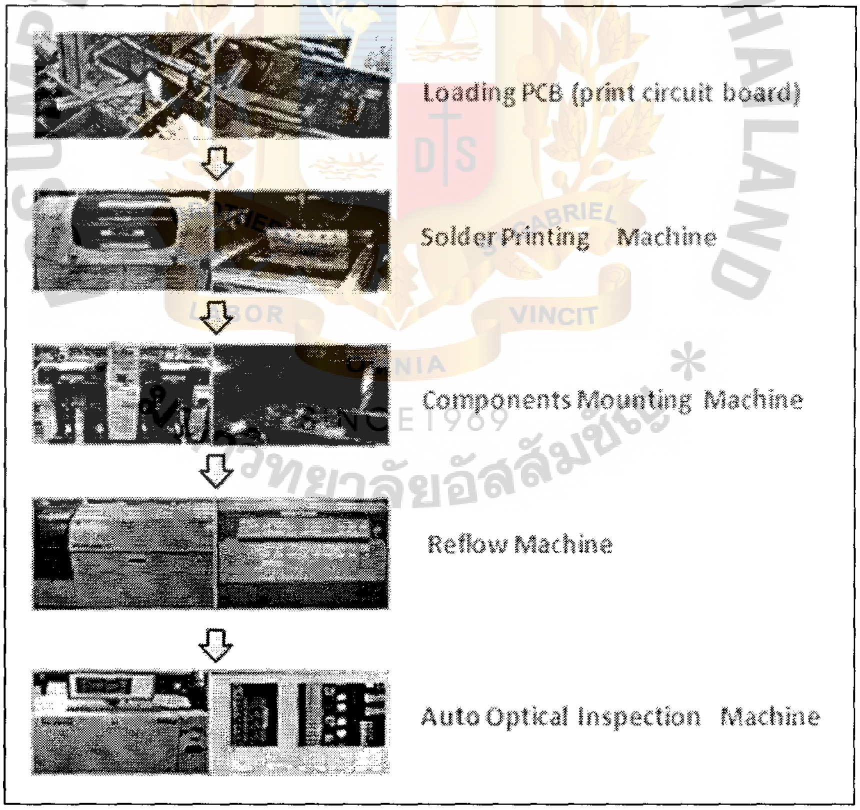
**Figure 1.2: Classification of data storage**




Source: Daim, T., U., Ploykiitikoon, P., Kenendy, E., and Choothian, W. (2008), The factory production of the SSD is based on each customer's precise specification. All materials and equipments used in the production are supplied by the customers themselves. The customers' account managers will send their purchase orders to the factory from around the world. These are coordinated by the Taipei sales department which will confirm the orders. The production department then commences production schedule planning. Then end customer requests the factory to ship the product. The company performs all transactions via the different systems of each customer, and both customer and end customer can monitor all transactions.

The following Figures illustrate the various processes used in the production of orders.

**Figure 1.3: Surface Mounting Technology (SMT) Process**

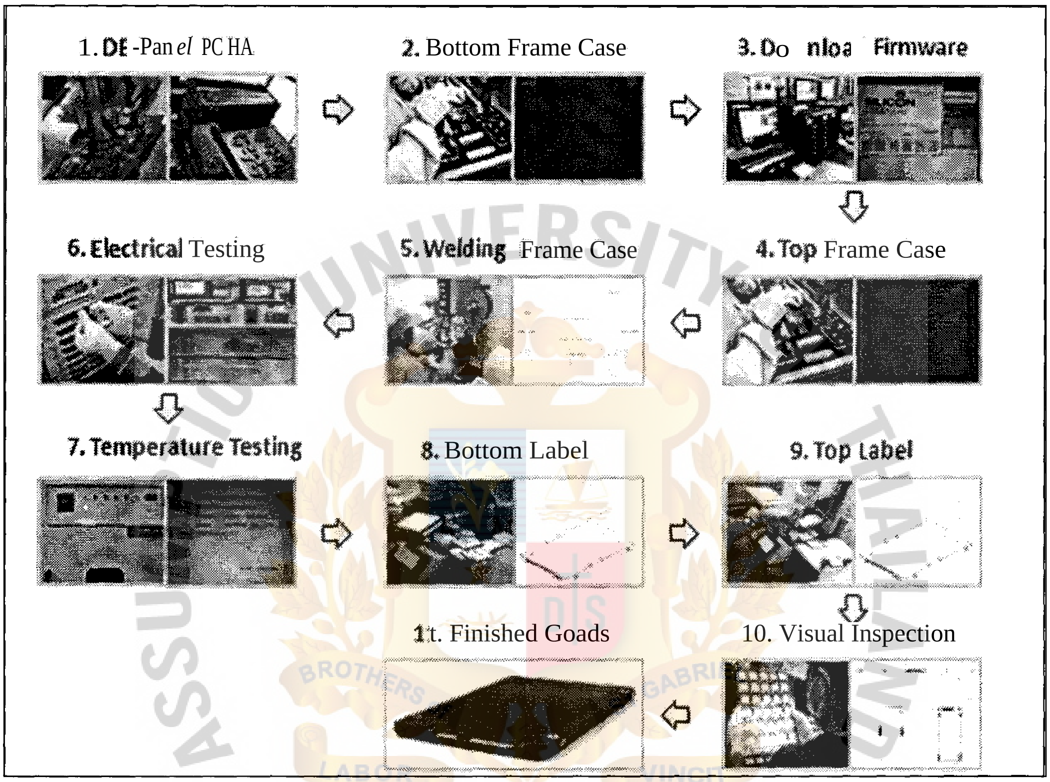



Source: Compiled from company standard procedures

The SMT process starts first. The Printed Circuit Board (PCB) is screened with solder paste and all components are placed in position by a components mounting machine.

After that, the PCB with components will go into the reflow oven to meld the components with PCB, and the item then pass through the Auto Optical Inspection (AOI) machine.

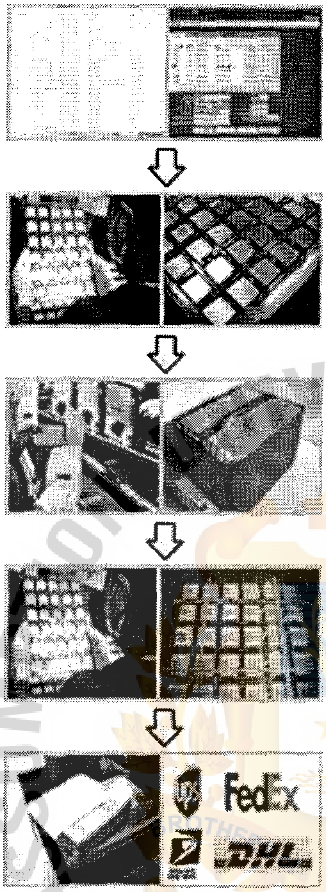
**Figure 1.4: Solid State Drive (SSD) Assembly Process**




Source: Compiled from company standard procedures

The PCB will be transferred to the assembly production process. The PCB is placed in a frame by an ultrasonic welding machine, and all units download firmware, based on the capacity of each model before undergoing an electrical test. Some models will be submitted to hot and cold temperature cycle testing (temperatures between -45 degrees and 90 degrees). Then, there is the inspection process, before all units are moved to the finished goods inventory.

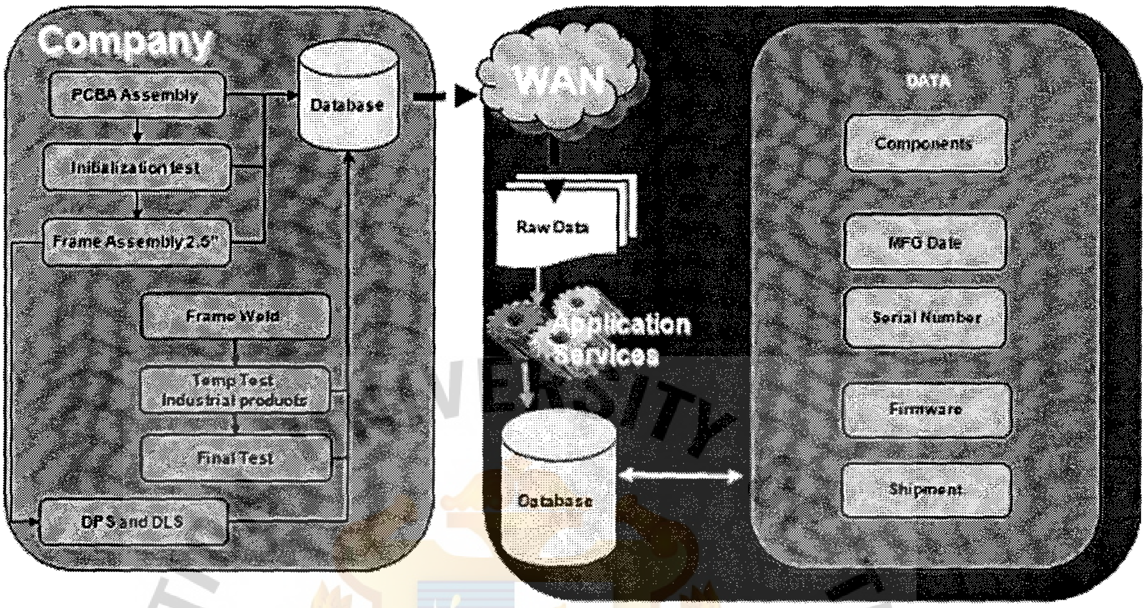
**Figure 1.5: Solid State Drive (SSD) Packing Process**




Source: Compiled from company standard procedures

Next, when an end customer requests delivery shipment, the packing process will start. Then the shipment process delivers the goods to the end customer, and into the customer's own system. Remaining inventory has to be stored until the next shipment request from a customer.

**Figure 1.6: Solid State Drive (SSD) Traceability System**




Source: Compiled from company standard procedures

Transactions between the company and a customer are controlled by a traceability system. Material usage information is recorded by this system. The production process uses the traceability system in order to collect data in all SSD units. Upon the completion of production, the company uses a barcode system (whose software is provided by the customer), to confirm the quantity of each serial number of SSD unit with direct interface to the customer's server. The customer can perform data validation, outward shipment; and billing transactions using this system.

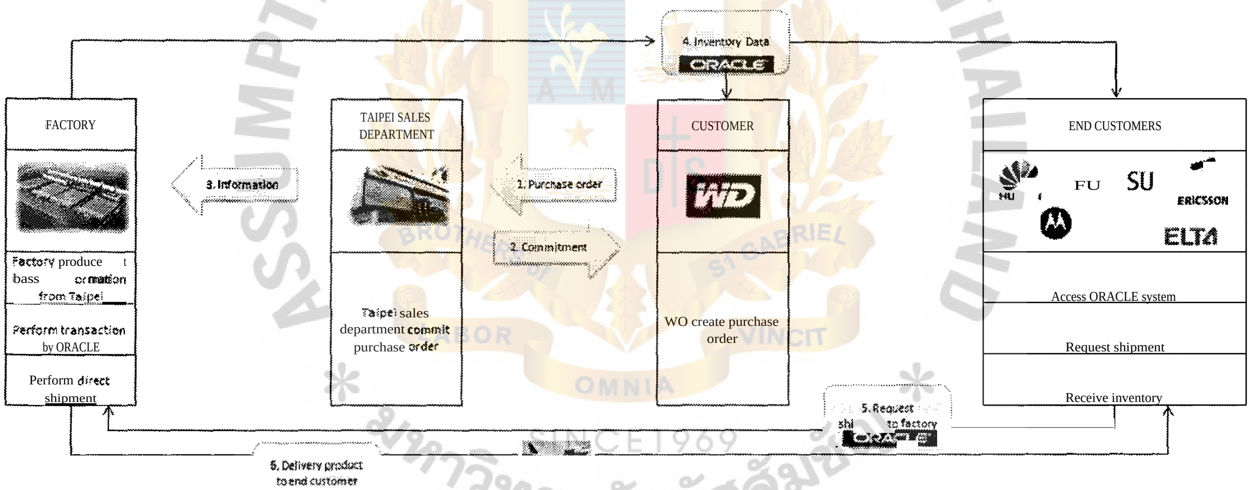
### 1.2 Statement of the Problem

The company management team is concerned about problems affecting the SSD business unit, because SSD is a new business unit for the company. Moreover, SSD will become a major future product as, it will soon replace hard drives. The company is the single source for each of its customer. Management team would like to gain the opportunity for developing a long term relationship with customers by fulfilling all requirements. The management team would like to find a solution to the problems, which occur in the SSD business unit, such as high demand fluctuation, short product life cycle, and pressure of cost reduction. In additional, there is no systematic forecasting approach for SSD. It affects decision-making, which will be a barrier to serving customer requirements and to effective internal operations.

*1.2.1 High Customer Demand Fluctuation*

The SSD product has many demand fluctuations over the year. The company sales department acknowledges an order from a customer and informs the factory. The factory creates a production schedule. However, actual demand from end customers changes frequently. The company needs to cover shortages by overtime production. Thus, the company incurs excess inventory cost for over production.

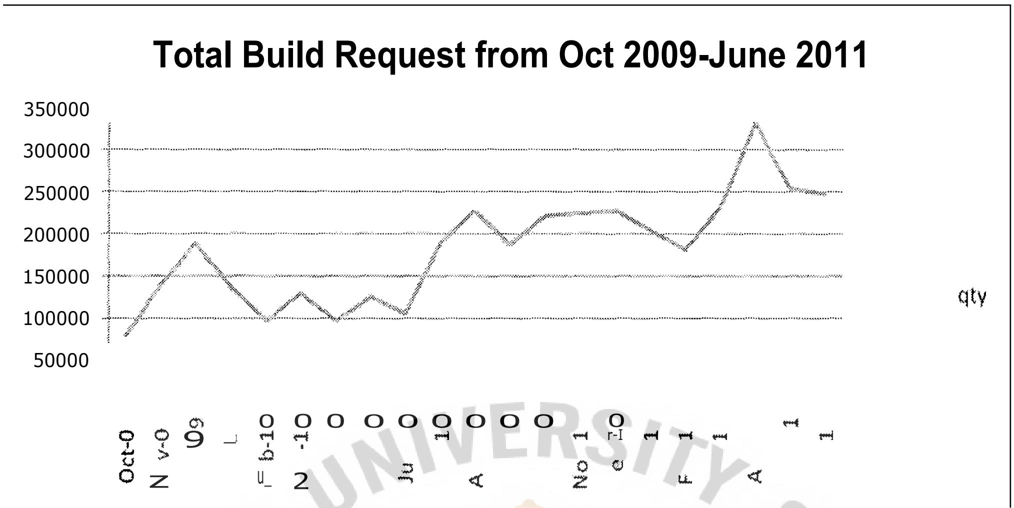
**Figure 1.7: Solid State Drive (SSD) Business Process**




Source: Compiled from company standard procedures

SSD production started in October 2009. The, line graph above shows the product build request quantity from ac customer (in the blue line). The actual demand quantity from end-customer is shown in red. In Figure 1.10, the 18 months historical data shows variance between production and actual demand.

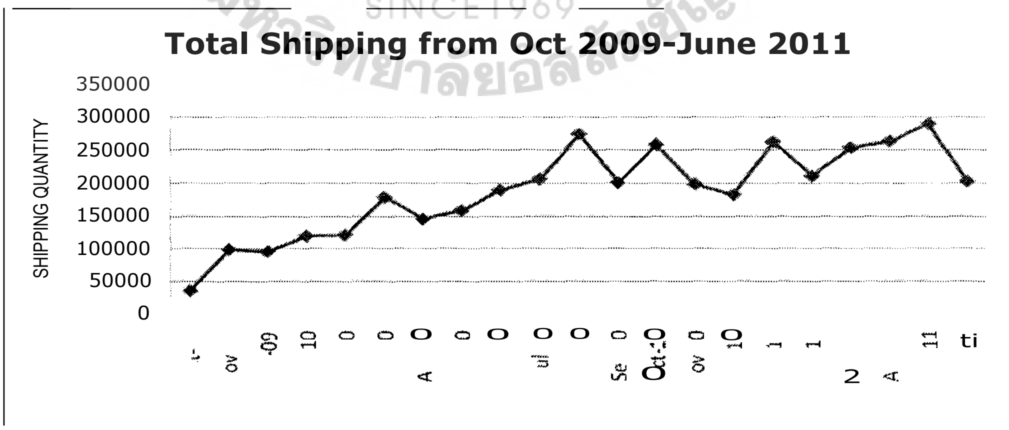
**Figure 1.8: Total Build Request Quantity from October 2009-June 2011**




Source: Compiled from company historical records

Figure 1.8 shows the increasing trends of the total build request from October 2009 to June 2011. The requested quantity dropped from January 2010 to July 2010, but the order rebounded again from July 2010 onwards and moved constantly in the period from August 2010 to March 2011. After the first quarter of the third year, the orders increased dramatically into highest volumes, but then dropped again. This illustrates that the request quantity will continuing growing year by year.

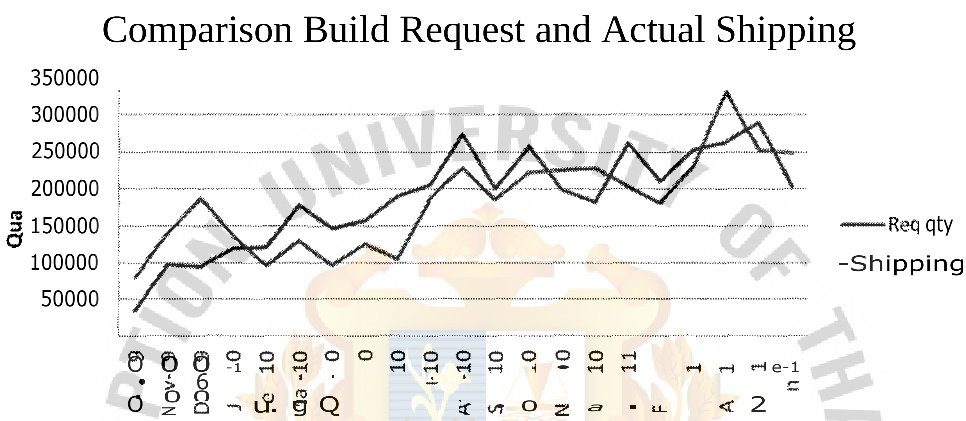
**Figure 1.9: Total Actual Demand Quantity from October 2009-June2011**




Source: Compiled from company historical records

Figure 1.9, the total actual shipping quantity, shows a monthly gradual increase. In the first year the shipping quantity increased, until the middle of the second year. Then, variation occurred in the shipping quantity month by month until the beginning of the third year. The trend shows that the highest shipment volume in the first year becomes the base line of the second year. Thereafter, the highest volume of the second year also becomes the base line of the third year.

**Figure 1.10: Comparison of Build Request and Actual Demand**




Source: Compiled from company historical records

The data trend shows a positive correlation between the build request and actual shipping quantity. However, some periods show negative correlations between the build request and actual shipping quantity. Most of the variance shows that the actual demand is higher than build request at the beginning. Results from some periods show that build request quantity is higher than actual shipping quantity. The factory will produced based on the build request, but the actual shipping quantity is sometimes less than the initial request.

The company has to carry excess inventory in stock. When the actual demand is higher than build request, the factory has insufficient finished goods to fulfill the request for delivery. The factory needs to set up overtime production in order to cover actual demand and prevent potential loss of sales. Consequently, the factory suffers high manufacturing cost and stock holding cost from holding excess inventory.

The company faces the situation of uncertain demand, because of the discrepancy and error of build requests. The way to measure error between actual demands and request quantity is Mean Absolute Deviation (MAD), which can define discrepancy quantity. The historical data 18 months shows MAD equal to 40319. The results are summarized in Table 1.1 below:



**Table1.1: Error of Build Request and Actual Demand (18 Months Data)**

| Quarter | Period | Month | Shipping | Req qty | Error | Absolute error | % Error | MAD | MSE | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | Oct-09 | 35433 | 79917 | -44484 | 44484 | 125.54 | 44484 | 1978826256 | 126.54 |
| | 2 | Nov-09 | 98625 | 139645 | -41020 | 41020 | 41.59 | 42752 | 1830733328 | 83.57 |
| | 3 | Dec-09 | 95586 | 187696 | -92110 | 92110 | 96.36 | 59205 | 4048572919 | 87.83 |
| 2 | 4 | Jan-10 | 119484 | 136305 | -16821 | 16821 | 14.08 | 48609 | 3107166199 | 69.39 |
| | 5 | Feb-10 | 121165 | 97160 | 24005 | 24005 | 19.81 | 43688 | 2600980964 | 59.48 |
| | 6 | Mar-10 | 178735 | 129958 | 48777 | 48777 | 27.29 | 44536 | 2564016759 | 54.11 |
| 3 | 7 | Apr-10 | 145490 | 97126 | 48364 | 48364 | 33/4 | 45083 | 2531882435 | 51.13 |
| | 8 | May-10 | 158546 | 125675 | 32871 | 32871 | 20.73 | 43557 | 2350459961 | 47.33 |
| | 9 | Jun-10 | 189719 | 105857 | 83862 | 83862 | 44.20 | 48035 | 2870723859 | 46.98 |
| 4 | 10 | Jul-10 | 206135 | 188996 | 17139 | 17139 | 8..31 | 44945 | 2613026005 | 43.12 |
| | 11 | Aug-10 | 273708 | 227724 | 45984 | 45984 | 16.80 | 45040 | 2567708028 | 40.72 |
| | 12 | Sep-10 | 200524 | 186276 | 14248 | 14248 | 7.11 | 42474 | 2370649484 | 37.92 |
| 1 | 13 | Oct-10 | 257668 | 221941 | 35727 | 36727 | 13.87 | 41955 | 2286477872 | 36.07 |
| | 14 | Nov-10 | 198605 | 224867 | -26262 | 26262 | 13.22 | 40834 | 2172421785 | 34.44 |
| | 15 | Dec-10 | 183060 | 227440 | -44380 | 44380 | 24.24 | 41070 | 2158899292 | 33.76 |
| 2 | 16 | Jan-11 | 261967 | 203604 | 58363 | 58363 | 22.28 | 42151 | 22368580⁷2 | 33.04 |
| | 17 | Feb-11 | 210635 | 181652 | 28983 | 28983 | 13.76 | 41376 | 21546 791 | 31.91 |
| | 18 | Mar-11 | 253444 | 231103 | 22341 | 22341 | 8.81 | 40319 | 2062714651 | 30.63 |

Source: Author's own

*1.2.2 Short Product Life Cycle*

SSD has a short product life cycle, around three to four months. Then it becomes obsolete in the market, as adaptation improvements are applied to newer versions. The company cannot sell its excess inventory as it is already obsolete. However, obsolete products can change their software and some components, to become a new version which can be sold to end customers. There will be cost involved in such modification, and the company has to absorb this cost,

*1.2.3 Pressure of Cost Reduction*

According to government policy, minimum wages will increase in the near future. The company needs an effective production plan in order to reduce overtime production, while still fulfilling demand from a customer, including unexpected demand.

*1.2.4 No Systematic Forecasting*

SSD product is a new business unit. There is no systematic forecasting for this product. The company cannot apply existing forecasting from other business units because SSD has different demand characteristics, and business transactions are also different.

## 1.3 Research Objectives

The company's management team would like to reduce cost, yet still have the SSD business unit fulfilling customer demand. The management team concludes that the SSD business unit requires systematic forecasting in order to accomplish its objectives:

1. To develop a suitable forecasting model for SSD manufacturing
2. To minimize variance gaps between production and actual demand.
3. To improve the efficiency and production of SSD manufacturing.

## 1.4 Scope of the Research

This research paper is a study of how to build and develop a forecasting model to fit an electronic manufacturing services company in Thailand. The forecasting technique will be applied to improve efficiency in production and minimize variation. This research focuses only on the exponential smoothing technique. The study will not look at all categories of product, but use aggregate forecasting. Inventory concern only the cost of products in order to calculate a comparison of over-production or shortage quantities due to forecasting error. The number of workers is fixed, but the cost of overtime is involved when shortages occur. The study focuses only on SSD products because its business transactions are different from other business units in the company. As SSD is a new product, there is no forecasting system, and demand characteristics are different from other products. The company cannot apply forecasting systems from other products.

### 1.5 Significance of the Research

This study uses a forecast model for solid-state drive production in the electronic manufacturing service industry in Thailand. The business is still in its early stage. Solid-state drive is the product for the future, replacing hard disks for memory storage. It is a challenge for a manufacturer in producing a new product. An effective forecasting system is necessary to reduce variations and improve efficiency in production. The company has implemented forecasting technique in this research report, which is therefore a real practical application.

### 1.6 Limitations of the Research

This study did not consider some factors such as material supply shortages, as all materials are supplied by customers. Quality problems regarding the materials and production processing, and production capacity is caused by customers because all equipment is provided by customers. In addition, all manufacturing procedures are defined by customer specifications and the company is not allowed to change or modify these constraints. Moreover, forecasting techniques focus only on the exponential smoothing technique and do not cover all models of exponential smoothing techniques.

### 1.7 Definition of Terms

| | |
|---|---|
| Autoregressive Integrated Moving average (ARIMA) | One of the time series forecasting techniques. |
| Electronics Manufacturing Service (EMS) | A firm which produces electronics product following customer requirements. |
| End of Life Product (EOL) | Obsolete product. |
| Mean Absolute Deviation (MAD) | An average squared error. |
| Mean Absolute Percentage Error (MAPE) | A measurement of forecast error. |
| Mean Square Error (MSE) | A measurement of forecast error. |
| Printed Circuit Board (PCB) | Circuit board without any electronics components. |
| Print Circuit Board Assembly (PCBA) | Circuit board with small electronics components such as integrates circuit or capacitor, which is ready for assembly production. |
| Surface Mounting Technology (SMT) | Printed circuit board production |
| Solid State Drive (SSD) | Data storage device that uses a memory store for persistent data. |

| | |
|---|---|
| Tracking Signal (TS) | The measurement of how good forecasting is in predicting actual value. |

# CHAPTER II

# REVIEW OF RELATED LITERATURE

## 2.1 Introduction to the Literature Review

The literature review of forecasting describes the important role of forecasting for business, and how forecasting techniques can help a company. Characteristics of forecasting and demand patterns are described. Moreover, elements of forecasting techniques are examined, for both quantitative and qualitative techniques. The measurement of forecast error is described. Finally, related researches and references show how forecasting has been implement and applied in business.

## 2.2 The Important Role of Forecasting

Forecasting is very important for all firms, whenever a company needs to know in detail about future event such as sales volume, investment, capacity planning, production, and work force. A forecasting technique can help a firm to predict the future, using a scientific method with reliable results. Quantitative and qualitative methods are techniques used in forecasting. Accurate forecasting is the key for managerial decision-making (Rieg, 2009).

The role of forecasting influences many type businesses. The marketing function needs to know future customer demand. Firms need to apply forecasting techniques to estimate the sales volume needed to fulfill customer requirements in the near future (Krajewski, and Ritzman, 2005). Production requires forecasting techniques to create production schedules in order to avoid over production and prevent flow interruptions so as to maintain efficiency. Capacity planning also needs forecasting techniques in order to predict the appropriate number of machines and equipment needed in the future (Anupindi, Chopra, Deshmukh, Mieghem and Zemal 2006). The Purchasing department uses forecasting techniques to make sure that material and inventory will not be in short supply when needed by other departments. Moreover, the work force requires forecasting technique by the human resource department in order to set up recruitment and training schedules (Chase, Aquilano and Jacobs 1998). Cash-flow is concerned with the company's liquidity, which needs a forecasting technique in the financial department (Heizer and Render 2008). The examples above show how the importance of forecasting impacts the functions of every department in an organization. The accuracy of forecasting has an impact on inventory cost, service level, scheduling, and other operations (Catt, Barbour, and Robb, 2008).

## 2.3 General Characteristics of Forecasting

Forecasts have four attributes, as described by Simchi-Levi, Kaminsky and Simchi-Levi. (2008) and Chase, Aquilano and Jacobs (1998) below.

*Forecasts are usually wrong*

*Forecasts should be accompanied by a measure of forecast error*

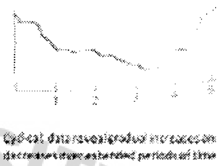
*Aggregate forecasts are more accurate than individual forecasts*

*Long-range forecasts are less accurate than short-range forecasts*

## 2.4 Demand Patterns Characteristics

Forecasting requires historical data, which is the previous demand from customers. Each business has different demand types, depending on many factors, such as customer requirement and product life cycle. Normally, the characteristics of demand are categorized into five types (Chase, Aquilano and Jacobs (1998). Firstly, the horizontal pattern appears with constant demand. Secondly, the trend pattern shows demand increasing and decreasing over time. Thirdly, in the seasonal pattern, movement of demand (both increasing and decreasing) will be repeated, which can be daily, weekly, monthly, quarterly, or yearly. Fourthly, the cyclical, demand pattern occurs every several years, as in a product life cycle or business life cycle: this pattern similar to a seasonal pattern but being cyclical is over a longer time. Figure 2.1 1 shows these four demand patterns.

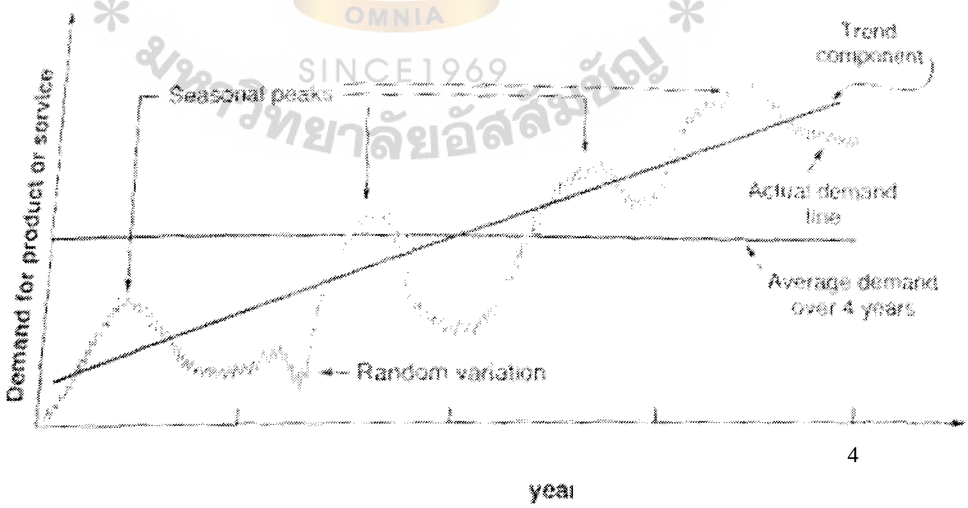
**Figure 2.1: Patterns of demand**



Source: Krajewski and Ritzman (2005)

The last, fifth, demand pattern is random, which is unpredictable: its, data platform contains high fluctuation without any trends or patterns. All five patterns occur continuously in time series, for example, when product demand over four years contains horizontal, trend, seasonal, and random patterns (as, shown in Figure 2.2).

**Figure 2.2: Example of product demand over four years.**

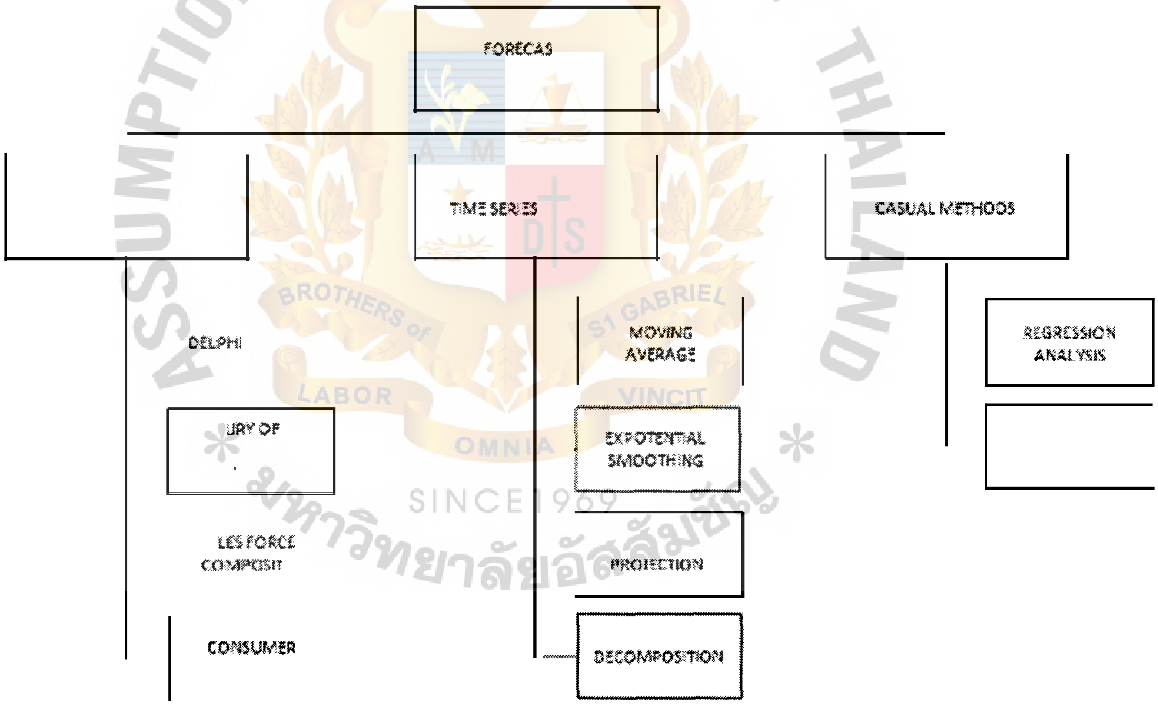



Source: Heizer and Render (2008),

## 2.5 Elements of Forecasting Technique

Forecasting technique can be divided into two types; qualitative and quantitative. Qualitative technique depends on experience and knowledge of the forecaster to make decisions based on personal subjective judgment. Quantitative technique uses historical data and related variables, in statistical formulae, the result being quantified numerical values for decision-making. The summary below describes the various categories of forecasting techniques available for forecasters.

**Figure 2.3: Categories of Forecasting Techniques**




Source: Render, Stair and Hanna (2006); Heizer and Render (2008); Wisner, Leong and Tan (2005); Curwin, and Slater (2008); Krajewski and Ritzman, (2005); Chase, Aquilano and Jacobs (1998)

*2.4.1 Qualitative model*

2.4.1.1 Delphi method

In this method, a group of experts acquire data from a questionnaire survey. They summarize all the data before input it into a forecasting model.

2.4.1.2 Jury of executive opinion

A group of top management provides opinions on the estimated demand. Each person comes from different departments. Opinions are based on each person's experience. Decisions are then made by the group.

2.4.1.3 Sales force composite

Salespersons will estimate the demand in their own region. Data will come from each region and be combined to become aggregate forecasting data.

2.4.1.4 Consumer market survey

This type of forecast obtains data directly from customers. Consumer market surveys not only help in forecasting but are also useful in acquiring data for new product design.

*2.4.2 Time series methods*

2.4.2.1 Moving average

This method assumes that the demand pattern is quite steady over time. Simple moving average uses historical data of actual demand for calculation. Moreover, this method removes the effect of random fluctuation. Simple moving average contains a constant weight. However, each period has its own weight. Putting weight in each period transforms the simple moving average method into another method called weight moving average method. There is no exact way to choose the weight number for each period: it has to be done by trial and error. Generally, the most recent past is the important period for indicating the present period, and its weight should be higher. The appropriate weight is given lower variance between actual and forecast numbers.

Furthermore, the double moving average method is also used for forecasting, as it provides forecasting more constant than one time average value.

2.4.2.2 Exponential smoothing

The moving average and weight moving average methods require large amounts of historical data. It is very difficult to implement. There is another type of moving average called exponential smoothing. This method requires less historical data in performing calculation. Exponential smoothing is easier to apply and more convenient for a forecaster. This method required three sets of variables for calculation: the most recent forecast, actual demand of this period, and smoothing constant alpha (a) which is a value between 0-1. Moreover, exponential smoothing has more advanced computation for trend and seasonal factors. Examples of this are double exponential smoothing method, linear exponential smoothing method, triple exponential smoothing method and Holt-Winters exponential smoothing method.

2.4.2.3 Trend projection

Another technique of time-series forecasting is called trend projection. This technique will fit a trend line to a series of historical data and then project the lines into medium to long term forecasting (for example, a linear trend line). The technique minimizes the sum of square error by the least-square method.

2.4.2.4 Decomposition

There are four types of demand patterns; trend, seasonal, cycle, and random variation. In practice, the time-series technique can be divided, similar to demand patterns. Decomposition has two forms of time-series model: additive model and multiplicative model. The additive model assumes that all components of patterns are added together for estimation. The multiplicative model assumes that the main components of patterns are multiplied together for estimation. For example, seasonal variation is one type of demand pattern, which can affect forecasting. Time variation occurs in seasonal periods. Adjustment are required for seasons with a trend line. A seasonal index is needed for calculation in order to indicate how each season compares with the average season. This index is often used in the multiplicative method, but also can be used in the additive model. A seasonal index is computed by CMA (center moving average). After acquiring a seasonal index from the calculation, the value will be used to find a decomposition method with trend and seasonal patterns.

2.4.2.5 Other time-series forecasting models

There are other forecasting techniques such as Box-Jenkins technology, neural network, and expert system, all requiring sophisticate computation and all are very complicated. For time-series forecasting methods, the period is divided into three types; short term forecasting, medium term forecasting and long term forecasting. The short term forecasting, which is around three months, is used for purchasing planning and scheduling. Medium term forecasting has a period from three months to three years, and contains several methods which are suitable for each pattern of demand.

*2.4.3 Casual methods*

2.4.3.1 Regression

The regression model is used to describe relationships between variables. This can be divided into two types; dependent variables (or response variables) and independent variables (sometimes called exploratory variables). Data is illustrated graphically by using a 'scatter diagram" in order to describe the result after computation. The relationship between the dependent and independent variables is classified by its correlation coefficient. Deviation of data can occur, both positively or negatively. The best regression line is defined as the one with the minimum square error. Consequently, sometimes regression analysis is called least-square regression. The measurement of the regression model uses the sum of the square total (SST) and sum of the Square Error (SSE). Moreover, the regression model can test significance by Mean Squared Regression (MSR).

2.4.3.2 Multiple regressions

When there is more than one independent variable, the multiple regressions model will apply. This means that problems become more complex for solving. Multiple regression can be used in forecasting both trend and seasonal demand. Multiple regression become more powerful than simple regression because it includes more than one independent variable, however, the model should be tested before implementing it in a business application.

2.4.3.3 Econometric models

Sometimes multiple regressions cannot compute, for example, when time-series data combines with cross-sectional data. An econometric model such as panel data regression will be applied. Panel data regression can be divided into two types: one-way and two-way type; and. fixed-effects and random-effects type.

*2.4.4 Measure of forecast accuracy*

Forecasting techniques require measurement in order to know how each model works and compares result between each model. Forecast error can defined in simple mathematic in the equation below.

Forecast error = actual value *minus* forecast value

There are three methods to measure forecast accuracy. First is the mean absolute deviation (MAD), which is computed by using thesum of absolute value of each forecast error divided by the number of error. The formula is below.

$$MAD = \frac{\sum |\text{forecast error}|}{n}$$

Where

n = number of forecast error

Instead of using mean absolute deviation, the other method used for computation of measure forecast accuracy, is mean squared error (MSE).

$$MSE = \frac{\sum (\text{error})}{n}$$

Where

n = number of forecast error

To describe the average of absolute percentage of actual value, the Mean Absolute Percentage error (MAPE) will be used in the computation.

$$\text{MAPE} = \frac{\sum \frac{|\text{error}|}{|\text{actual}|} 100\%}{n}$$

The monitoring forecast model needs to perform continually in order to realize a performance result. One way for monitoring a forecast model is to use a tracking signal. It measures performance of prediction in actual values. The formula for a tracking signal is below.

$$\text{Tracking signal} = \frac{\text{RSFE}}{\text{MAD}}$$

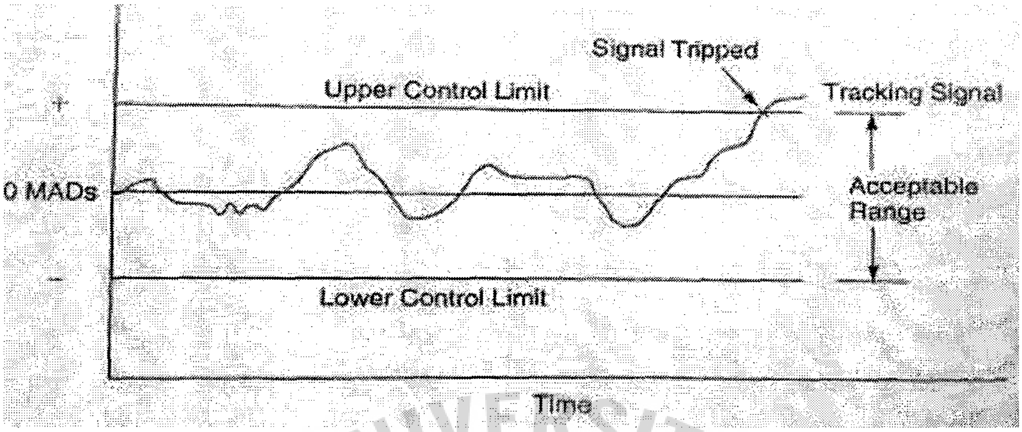
Where

RSFE = running sum of the forecast errors

MAD = mean absolute deviation

RSFE, it computed by the summing together the deviation between actual demand and forecast value in each period. Positive values of a tracking signal indicate that actual demand is more than forecast value. On the other hand, negative value means actual demand is less than forecast value. A tracking signal should not exceed the upper limit and not be less than the lower limit. However, there is no exact value in determining the limit of a tracking signal. The acceptable range will be a reasonable value, not too high and not too low. Figure 2.4 shows an example plot of a tracking signal.

**Figure 2.4: Plot of tracking signal**




Source: Render, Stair and Hanna (2006); Heizer and Render (2008);
Krajewski and Ritzman, (2005); Chase, Aquilano and Jacobs (1998)

Render et al.(2006) state that the maximum for high volume stock item should be $^{+}$4 and for low volume stock items should be $^{+}$8.

## 2.6 Literature Review of Exponential Smoothing Forecasting Technique

One of the most popular forecasting methods is the exponential smoothing technique (Chipulu, Ojiako, and Kaparis (2011); De Gooijer and Hyndman (2006) also stated that the method is widely used in business and industry. Wilmer (2006) stated that one of the most widespread forecasting techniques is exponential smoothing because the method is simple, reasonably accurate, and efficient from the computation point of view. Moreover, exponential smoothing provides low forecast error (Rieg, 2009). Another reason of using exponential smoothing is the small data requirement mentioned by Shoesmith and Pinder (2001). A survey by Mentzer and Kahn (1995) found that 92% of respondents choose exponential smoothing techniques for periods of three months to two years

Many research reports prove that exponential smoothing performs better than, or provide equal results to, other sophisticated forecasting model, Hyndman (2001) concluded that simple exponential smoothing is more robust than ARIMA forecasts because they are applicable to a larger class of stochastic processes than an ARIMA process. Moreover, Rieg (2009) described exponential smoothing methods as providing minimum forecast error when compared with complex model like neural network and Box-Jenkins. Athiyaman and Robertson (1992) found that forecast accuracy of econometric and regression models are not superior to simple time series forecasting techniques, and that Brown's one parameter exponential smoothing method performs as well as complex model like the Box-Jenkins method. Fildes and Beard (1991) stated that simple exponential smoothing has performed well in comparative testing with other models.

Many cases indicate that the exponential smoothing model provides successful results in many types of businesses. Miller and Liberatore (1993) applied seasonal exponential smoothing in production planning by using Winters' four parameters, which provide the most accurate forecast in model evaluation. For call center arrival time, exponential smoothing for double seasonality is the most accurate for short-term prediction, based on a study by Taylor (2008). The tourism industry also implements the exponential smoothing technique in demand forecasting of Thai tourist arrivals in Hong Kong. The results show that the single exponential smoothing method performance is superior to other model for forecasting one month ahead. MAPE had an optimal value of 19.82, when compared with other models (Athiyaman and Robertson, 1992). Table 2.1 is a summary of exponential smoothing forecast techniques.

**Table 2.1: Summary of exponential smoothing forecast techniques**

| Ai to | onential Smoothing Research and Approches |
|---|---|
| De Gooijer and Rob J Hyndm (2006) | O.. of the m.. read fore.. ..niques is the ex..onential smoothing |
| Udechuk..u anc ..n ..ep (20.. | ..ponen..al provides o.. more compare ..th cc ..wo ..ai.. and |
| ..besmith and ..Prd r | Exponential smoothing is small data ..equr 1 |
| r J and K Kahn (19.. | Survey found that 92 of respondents choose exponential smoothing techniques for 1- .. ..s lt |
| ..a. F. .. 2001) | Single exp..ential smoothing more robust than ARIMA forecast because 1 are applica ..s larg.. r class of stochastic process..s than an ARIMA process |
| Hyndman and R.W. Roberson | Forecast accuracy of econometric and regression models are not superior to simple time se.. ..sing techniqu.. Brown's one parameter exponential smoothing method performs equally as complex model i.. ..Jenkins method |
| ..ert Fildes and Charles Bea.. (1991) | Simple exponential smoothing has performed well in comparative testing with other model |
| Miller 1 and Liberatore M. (1993) | Appl.. seasonal exponential smoothing in production planning by using Winters for para..eters |
| .. W. Taylor (2008) | Case at call .. enter annual time, exponential smoothing for double seasonality is the mo..t .. ..term prec |
| A. Athiyaman ad R.W. Robertson. 1.. | De..and forecasting of Thailand tourist arrival .. Hong Kon.. the results show that ..ponential smoothing method .. form superior than other mode.. ..re month ahead f.. |

Source: Author's own

## 2.7 Summary of the Literature Review

This chapter has described the importance of forecasting to a business, to match supply with demand so as to avoid excess inventory or being out-of-stock or the cost of having urgently to meet sudden change in demand. The range of forecasting techniques has been described and explained, and especially the exponential smoothing technique. The literature has shown how exponential smoothing forecasting has been successfully applied to many businesses. This technique does not require large data and sophisticated software for calculation. Exponential smoothing provides more accurate results than complex models such as econometric, Box-Jenkins, and artificial neural network for short term prediction. Moreover, this technique is widely used because it does not involve complex computation. Therefore, this technique has been chosen to be tested in this case study, as explained in the next chapter.

# CHAPTER III

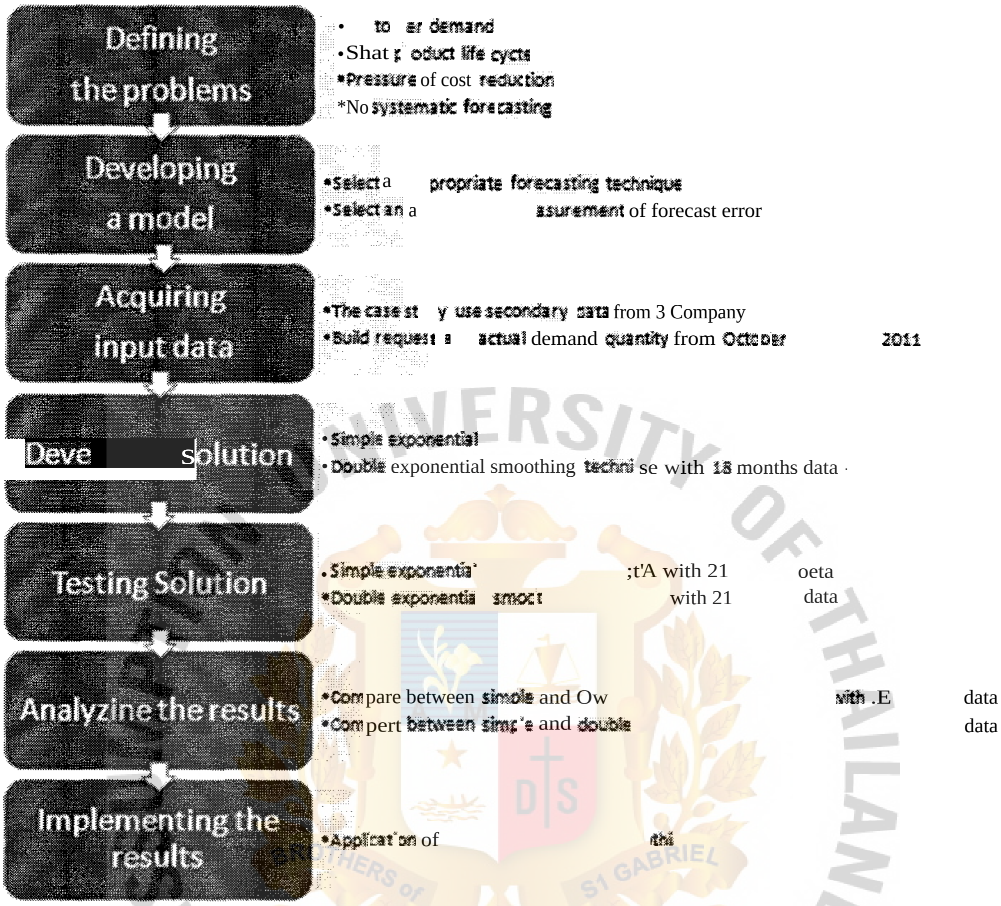
# RESEARCH METHODOLOGY

There are many forecasting techniques reviewed in Chapter II. In order to select appropriate technique for this case study, a research framework is required. The framework will determine the sequential procedure, beginning with defining the problems. Techniques are then selected which will suitable for this case study. Data collection is required for analysis in selecting an appropriate forecast technique. The simple exponential smoothing technique and double exponential smoothing technique are used to forecast the demand of SSD production. Consequently, both techniques will be applied in this case study, testing solution by comparing both forecasting techniques for between 18 months data and 21 months data. Mean square error is used to measure forecast error in both techniques. The case study uses Microsoft Excel, which is widespread commercial software for calculation and user friendly. It will be used for computation and also use the SOLVER function for finding optimal a and $\beta$ values.

## 3.1 Research Framework

The framework defines both the exponential smoothing technique and double exponential smoothing technique. The case study uses the forecasting steps from Render et al. (2006) in order to develop research framework, which is shown in Figure 3.1

**Figure 3.1 Research Framework**




Source: Render et al. (2006)

### 3.2 Defining the problem

According to the problem statement in Chapter I, customer demand fluctuation, short product life cycle, and pressure of cost reduction, are problems which the company cannot control. Therefore, the company has to create systematic forecasting in order to reduce variance between actual demands, and to reduce inventory cost and production cost.

Table 1.1 in Chapter I shows a comparison between actual demand and build request, with both positive and negative variance. When a build request is less than actual demand, it means the company is left with excess stock. On the other hand, sometimes a build request is higher than customer demand, which means over production. Then measurement of error in historical data, using MAD computation of historical data, is equal to 40319. In the beginning, the company produces more than actual demand following a build request, which can be indicated by a tracking signal. However, actual demand starts increasing rapidly later, so the company needs to build products based on build requests. This leads to shortage and inability to fulfill customer demand.

### 3.3 Developing a model

Wilson and Miller (1998) recommend a way to select a forecasting method, as shown in Table 3.1.

**Table 3.1: A guide to selecting an appropriate forecasting method**

| *Forecasting Method* | | *Quantity or Historical Data ofObservations)* | *Forecast Horizon* |
|---|---|---|---|
| Simple Exponential Smoothing | Stationary | 5 to 10 | Sho11 |
| Exponential Smoothing | 1 inear trend | 10 to 15 | Short to medium |
| Winters' Exponential Smoothing | frond and seasonality | Al least 4 or 5 season | Short to medium |
| Jecomp...iti on | C.111 11411,11V trend, seasonal, pattern | Enough to see peaks .11111 troughs 711 the cycle | Short, medium, and cyclical and long |
| egression rend | Linear and nonlinear trend with or without seasonality | Minimum of 14) with per if seasonality Is included | Short to ium |
| ure ss it Based: Causal | an handle nearly all data | Minimum of 10 per independent patterns | Sh rt, medium, varta the and long |

Source: Wilson and Miller (1998)

According to historical data, the length of time for observation and collecting data is 18 months. In Figure 1.9 in Chapter I, the actual demand pattern become a trend line.

The reason is that the product contains the latest technology, which is quite new to the market. Moreover, the company needs to forecast short to medium periods because of rapid obsolescence of the product as improved versions are introduced. Due to limitations in historical data and actual demand pattern in this case study the appropriate forecasting techniques are simple exponential smoothing and double exponential smoothing (Holt's method). Figure 3.2 described how both forecasting techniques are suited to minimum quantity of historical data and fit the short to medium term forecast horizon.

### 3.4 Acquiring input data

The research methodology in this study uses only secondary data, which are build request quantity and actual shipping quantity. Company record data is on the ERP system and customers allow the company to acquire data from their system which is updated every day in the customer's database. The database connects with all regional end users around the world. The company uses the customer's system for shipping transactions and finished goods inventory control. Moreover, the company's ERP is used for manufacturing order control and performing transactions in billing invoices. All information in this case study is secondary data only, but it is solid based on real transactions, with a traceability system. All serial numbers of products are recorded in the customer database and are used to perform financial transactions with the customer. Data validation is performed by the customer. If there is any discrepancy in quantity and model, the company will receive feedback within 24 hours

### 3.5 Developing solution

Simple exponential smoothing and double exponential smoothing are implemented in this study, using Microsoft Excel for computation.

*3.5.1 Simple exponential smoothing*

Simple exponential smoothing contains a (alpha) value in its equation; it is called a "smoothing constant". It can change to a high or low range of a value between 0-1. Selecting a smoothing constant affects the forecast accuracy. One a value is given the lowest MAD, and it will be an appropriate value for exponential smoothing. The equation for simple exponential smoothing is shown below.

$$F_t = F_{t\text{-}1} + \mathrm{a}\,(Y_{t\text{-}1} - F_{t\text{-}1})$$

Where

$F_t$ = new forecast (for time period *t)*

$F_{t-1}$ = previous forecast (for time period t-1)

a = smoothing constant (0 < a < 1)

$Y_{t-1}$ = previous period's actual demand

**Table 3.2: Spreadsheet formula of simple exponential smoothing formula.**

| Destination cell | Formula | Description |
|---|---|---|
| C6 | None | Period |
| E6 | None | Actual demand |
| F6 | None | Forecast value (use actual demand of 1st period) |
| F7 | $E$2*E6+(1-$E$2)*F6 | Forecast value |
| G6 | E6-F6 | Error |
| H6 | ABS(G6) | Absolute error |
| 16 | (H6/E6)*100 | Percentage of error |
| J6 | SUM($H$6:H6)/(C6-1) | MAD |

Source: Author's own

To begin, a value has to be chosen based on experiment by start from a low value and using MAD as a measurement. Then select medium 0.5 and highest value 0.9, using MAD for measurement. After acquiring MAD from three experiments, comparing which a value provides the lowest MAD mean providing the lowest error for simple exponential smoothing in this case study. Spreadsheet details are in Table 3.2 above.

**Table 3.3: Results of 18 Months Simple Exponential Smoothing Forecasting**

| | | Simple Exponential Smoothing 18 Months | | | |
|---|---|---|---|---|---|
| | | | Alpha OA | Alpha 0.5 | Alpha 0.9 |
| Quarter | Period | Month | MAD | MAD | MAD |
| | | Oct-09 | | | |
| | | Nov-09 | I 2 | 6319f | 63192 |
| | | Dec 09 | 66313 | 466⁷ : | 33236 |
| 2 | d | Jan-10 | 63126 | 43309 | 30233 |
| | | Feb-10 | 64042 | 37674 | 23700 |
| | | Mar-10 | 74771 | 43730 | |
| | 7 | Apr-10 | 74421 | 36664 | 30038 |
| | 8 | May-10 | 74998 | 33258 | 27220 |
| | | Jun-10 | 78347 | 33836 | 27843 |
| | f | Jul-10 | 81644 | 34006 | 26931 |
| | 11 | Au -10 | 89969 | 39130 | 31192 |
| | 12 | Sep-10 | 88611 | "3351 | 34377 |
| | 13, | Oct-10 | 91624 | 3:643 | 35722 |
| | 14 | Nov-10 | 3c its | 38604 | 37129 |
| | 15 | Dec-10 | 346.18 | 38319 | 35973 |
| | 16 | Jan-11 | 3620= | 39371 | 38696 |
| 2 | 17 | Feb-11 | | 38662 | 39006 |
| | | Mar-11 | 83712 | 38302 | 38973 |

Source: Author's own

Forecasting by using a value of 0.1 provides MAD equal to 83712 in period 18. This result shows that MAD is very high, which leads to high forecast error. In the next step, the model uses a value of 0.5 A smoothing constant 0.5 given to MAD is less than smoothing constant 0.1 in period 18, which means lower forecast error. There is a big gap in MAD between using 0.1 and 0.5' the lowest value of a cannot apply in this case study. The trend of an appropriate a will be a medium to highest smoothing constant. Then the highest smoothing constant value, equal to 0.9, will perform in the computation. Using a 0.9 provides the lowest MAD in period 18. The highest smoothing constant gives the best result when compared with the lowest a and medium a. However, the result is not optimal value because computation is based on the experiment using low, medium, and high smoothing constants only. Theoretically, alpha value can be any numbers between 0-1; a value between 0.2 to 0.4 and 0.6-0.8 were not used in this experiment.

Microsoft Excel contains a function called "SOLVER", which can find maximum and minimum target depending on objective function. In this case, SOLVER is applied to find optimal a value with minimum value of MAD as an objective function, changing value allows only a, and range of a is between 0-1. The SOLVER option can change based on the user, but for this case will still use the default setting without any changes. Maximum time is 100 seconds with 100 iterations. Precision remains 0.000001 and convergence still uses 0.0001, tolerance is 5%.

**Table 3.4: Results of 18 Months by Optimal a Value by SOLVER**

| | | | Simple [illegible] ntial Smoothing 18 Month | | | |
|---|---|---|---|---|---|---|
| | | | Alpha 0.1 | Alpha 3.5 | Alpha 0.9 | Alpha 0 649514222612607 |
| Quarter | P4 rio | Month | MAD | MAD | MAD | MAD |
| 1 | 1 | Oct-35 | | | | |
| | 2 | Nov-09 | 3132 | 63192 | 32 | [illegible] |
| | 3 | -09 | | 6670 | [illegible] | 1 [illegible] |
| | | [illegible]10 | | | | |
| | | Feb-10 | 340.2 | 7674 | 23704 | a. |
| | | Mar-10 | *74771* | *43730* | 30556 | |
| | | | 74421 | 3 Cif | 30030 | |
| | | | | | | |
| | 9 | Jun-10 | 78347 | 33836 | 27843 | |
| 4 | 10 | Jul-10 | 81644 | 34005 | 26531 | [illegible] |
| | | Aug | 39959 | 39130 | 31132 | 34810 |
| | 2 | 0 | [illegible]1 | 351.[illegible]1 | 34377 | |
| | 1 | [illegible] 0 | [illegible] | 38843 | 35722 | |
| | 14 | Nov-10 | 38670 | 38604 | 37129 | 690 |
| | [illegible] | [illegible] 0 | | 9 | 36973 | 1 |
| 2 | 9 | 1 | 36206 | [illegible] 71 | 381[illegible] | |
| | 1 | Feb-11 | 33637 | | 39006 | |
| | 18 | Mar 11 | *83112* | 38302 | 38973 | 37627 |

Source: Author's own

Optimal a value for simple exponential smoothing by SOLVER is 0.649514222612607. MAD is equal to 37627 in period 18. However, actual demand trend, shown in Figure 6, has a trend pattern. Simple exponential smoothing technique only adjusts data but it does not include trends in its computation.

*3.5.2 Double exponential smoothing*

Double exponential smoothing (or Holt's method), includes trends in its computation. Instead of containing a in equation, the other value, which is β (beta), represents a trend smoothing constant. Similar to a smoothing constant, β can be any number between 0-1. Forecasting is performed by simple exponential smoothing, and then adds the trend value in that period. Double exponential smoothing can be written mathematically, as below.

Forecast including trend *(FIT)* = new forecast $(F_t)$ + trend correction (T1)

$T_t$ is computed by

$$T_t = (1- II)\ T_{t-1} + \beta\ (F_t - F_{t-1})$$

Where

$T_t$ = smoothed trend for period $t$

$T_{t-1}$ = smoothed trend for preceding period

13 = trend smooth constant that we select

$F_t$ = simple exponential smoothed forecast for period $t$

$F_{t-1}$ = forecast for previous period

According to optimal a from simple exponential smoothing using SOLVER, only 13 value will change in the study. Base on the previous experiment, choosing β uses the same assumption by starting from lowest, to medium and highest value.

**Table 3.5: Spreadsheet formula of double exponential smoothing formula.**

| Destination cell | Formula | Description |
|---|---|---|
| C6 | None | Period |
| E6 | None | Actual demand |
| F6 | None | Forecast value<br>(use actual demand of 1st period) |
| F7 | None | Forecast value<br>(use actual demand of 1st period) |
| F8 | $E$2*E7+(1-$E$2)*F7 | Forecast value |
| G8 | (1-$E$3)*G7+$E$3*(F8-F7) | Trend |
| H7 | F7+G7 | Forecast with trend |
| 16 | E7-H7 | Error |
| J6 | ABS(I7) | Absolute error |
| K6 | J7/E7*100 | Percentage of error |
| L6 | SUM($J$7:J7)/(C7-1) | MAD |

Source: Author's own

**Table 3.6: Results of 18 Months Double Exponential Smoothing Forecasting**

| | | | Doubt Exponential Smoothing 18 Month | | |
|---|---|---|---|---|---|
| | | | Alpha 0.619514222612607 | | |
| | | | Boa 0.1 | a a 0,6 | Beta 0,9 |
| uarter | Period | Month | MAD | MAD | MAD |
| | | Oct-09 | | | |
| | | Nov-09 | 92 | 63192 | 53192 |
| | | 0S | 39098 | 32303 | 10511 |
| 2 | | Jan-1( | | | 32251 |
| | | I " | | | 25930 |
| | 6 | Mar.% | | | 31290 |
| | | | | | 18! |
| | | | _80 | 4 | 31022 |
| | | | 26727 | 24837 | 30815 |
| 4 | 10 | Jut. 10 | 26873 | 23571 | 23267 |
| | 11 | | 30009 | 27294 | 31326 |
| | 12 | Sep-1 | 32765 | 32045 | 36952 |
| | 13 | Oct-1( | 32628 | 32640 | 39138 |
| | 14 | Nov-10 | 3446 | 34662 | 41239 |
| | 15 | Dec-10 | 347 | | 2 |
| 2 | 16 | Jan-11 | 36650 | 82 | a2 |
| | 1/ | Feb-11 | 36621 | 31411 | 43572 |
| | 18 | ar-1 | | 0 | 436 |

Source: Author's own

Double exponential smoothing with β equal to 0.1 also gives a lower MAD than the original data, which is 36063 for period 18. Even simple exponential smoothing with optimal **a** value, still has higher MAD when compared with double exponential smoothing with 13 equal to 0.1. Selecting (3 value 0.5 shows the result of MAD equal to 37260. It provides the higher error when compared with β value 0.1. However, this forecasting technique with β value 0.5 is still better than the original data. Then, in the experiment of highest β using 0.9, the results show MAD has worse value. It means the highest error; even the original data given MAD less than this technique with a smoothed trend of 0.9.

Due to the experiment of using lowest to highest β value, the result of applying 0.1 as 13 value for a smoothed trend gives better result than medium and highest β value. Meanwhile, 0.1 might not be the optimal value for β. Next, SOLVER will be implemented to find the optimal 13 value. The SOLVER setting still uses standard the parameter without any changes.

**Figure 3.7: Results of 18 Months by Optimal 13 Value by SOLVER**

| | | | Double Exponential Smoothing 18 Months | | | |
|---|---|---|---|---|---|---|
| | | | Atka 0.649 26 | | | |
| Nurser | Period | Month | Bota 0.1 MAD | Bota 0.5 MAD | R 9 MAD | a 0.224519187857578 MAD |
| 1 | | | | | | |
| | 2 | Nov-1 | 63132 | 53112 | 63192 | |
| | | | | | | |
| 3 | - | Jan-10 | 9 | - | 1 | |
| | 5 | Feb-10 | 27458 | 21126 | 5 0 | |
| | | Mar-10 | 33(32 | 2 | 31 30 | |
| | | Apr-10 | 31139 | 28 36 | 34 36 | |
| | | May 10 | 0 | 4 4 | 31022 | |
| | | Jun-10 | 26727 | 24837 | 308 | |
| | 10 | Jul-10 | 2 73 | 23671 | | |
| | 11 | Aug-10 | 30( P3 | 27294 | 31326 | 2 85 |
| | 12 | - 0 | 32766 | | 36952 | 31586 |
| 1 | 13 | Oct-10 | 32628 | 32640 | 39138 | |
| | 14 | Nov-10 | 34446 | 34652 | 41235 | |
| | 15 | Dec 10 | 34751 | 33E37 | 38812 | |
| 2 | 16 | Jan-11 | 36650 | 37(32 | 42132 | 0 |
| | 17 | Feb-11 | 36621 | 37431 | 4 72 | 36133 |
| | 18 | Mar-11 | 36063, | 37260 | 43684 | 35777 |

Source: Author's own

After optimizing by using SOLVER, f3 value is 0.224519187857578. MAD is equal to 35777. The result is nearly the same as using 0.1 β value.

### 3.6 Testing the solution

Developing a solution by using exponential smoothing and double exponential smoothing, the result is lower MAD in both techniques, when compared with original historical data with optimal a and (3 value using the SOLVER function in Microsoft Excel. The next step of the forecasting procedure is testing the solution, in order to validate both techniques for solution reliability. Forecasting is performed for 18 periods, a year and a half Testing the solution will look at the next three periods to see if both techniques still provide constant results or not.

The result of the next three periods of testing, in Figures 3.8 and 3.9, shows that double exponential smoothing with optimal value of a and f3 gives the lowest MAD. Then exponential smoothing with optimal a value still performs better than the original data. Consequently, double exponential smoothing with optimal value of a and f3 still gives the same result, when compared with last 18 periods. The next steps are analyzing the result and implementing the result, which will be shown in chapter 4.

**Figure 3.8: Results of 21 Months by Optimal *a* Value by SOLVER**

| | | | Simple Exponential Smoothing 21 Months | | | |
|---|---|---|---|---|---|---|
| | | | U,1 | Al .5 | Alpha 0.9 | Alpha 0.671570593 1 1) |
| Quarter | Period | Month | 1.110 | IAD | MAI) | MAD |
| 1 | 1 | Oct 09 | | | | |
| | 2 | Nov-09 | 63192 | 3192 | 63192 | r, |
| | 3 | Dec-09 | 58613 | 45875 | 33136 | 1 |
| | 4 | Jan-10 | 63126 | 43309 | 3023 | |
| | 5 | Feb-10 | 54042 | 37674 | 3700 | |
| | 6 | Mar-10 | 14711 | 43730 | 30556 | 37114 |
| | | . 0 | 71.121 | 31 s1 | 30038 | 127 |
| | | May-10 | 74938 | 33258 | 27220 | 29562 |
| | 9 | Jun-10 | 78347 | 33836 | 27E43 | |
| 4 | | Jul-10 | 81644 | 34005 | 28E31 | |
| | 11 | 10 | 89559 | 35110 | 31132 | f |
| | 12 | Sep- 0 | 386' I | 3$3 I | 34377 | |
| 1 | 13 | Oct-10 | 31624 | 38E.3 | 35722 | [illegible] |
| | | Nov 10 | 38670 | 3 6 | 37129 | |
| | | Dec 0 | 34648 | 3.. | 36973 | 1 |
| | | Jan-11 | | 39671 | | |
| 2 | | Feb- 1 | 3637 | 38 2 | 3 | |
| | 18 | Mar-11 | 83111 | 38 | 38973 | 37627 |
| 3 | 19 | Apr-11 | 33819 | 37631 | 37574 | 36709 |
| | 20 | May-11 | 34835 | 37711 | 37039 | 36509 |
| | 21 | Jun-11 | 80894 | 39187 | 39391 | |

Source: Author's own

**Figure 3.9: Results of 21 Months by Optimal β Value by SOLVER**

| Double. xponential Smoothing 21 Months | | | | | | |
|---|---|---|---|---|---|---|
| | Alpha 0.671570593346307 | | | | | |
| | | | Dew 0.1 | Dew 03 | Beta 0.9 | .138085 23 |
| Quarter | Period | Month | MAU | MAU | MAU | MAL1 |
| | | Oct-09 | | | | |
| | | Nov-09 | 63192 | 03192 | 63192 | 63192 |
| | 3 | Dec-09 | 39096 | 32303 | 1 | 36543 |
| | | Jan-10 | 34619 | 26246 | 1 | 31249 |
| | 5 | Feb-10 | 27458 | 21125 | 25930 | 23497 |
| | 6 | Mar-10 | 33032 | 2651 | 31230 | 28931 |
| | | Apr-10 | 31109 | 28585 | 341 | c |
| | 8 | May-10 | 26780 | 24584 | 31022 | 2 |
| | | Jun-10 | 2E727 | 21337 | 30C 5 | 25034 |
| 4 | 10 | Jul-10 | 25373 | 1 | 282-7 | |
| | 51 | 1st 1 | | 94 | 1 | |
| | 12 | Sep-10 | | 045 | 2 | 31 |
| 1 | 13 | Oct-10 | 32.323 | 32E40 | 39138 | 31476 |
| | 4 | Nov-10 | 34446 | 31502 | 41239 | 33091 |
| | | U c 13 | 34761 | 1 | | 33751 |
| 2 | | •11 | 6650 | 3 | 2132: | 36098 |
| | 17 | F0-11 | 33321 | 37431 | 43572 | 6133 |
| | 8 | Mar-11 | | 3 2 0 | 436841 | 35777 |
| 3 | | 4111 | 34336 | 35827 | 414471 | 34698 |
| | 20 | Ma -11 | 3.1346 | 36076 | | 34 [illegible] |
| | I | .6.i 1' | 36f,54 | 37911 | 43[illegible] | |

Source: Author's own

# CHAPTER IV

# PRESENTATION AND CRITICAL DISCUSSION OF RESULTS

In Chapter III, simple exponential smoothing and double exponential smoothing techniques were developed and tested with two conditions; application of 18 months data and application of 21 months data. The results show that double exponential smoothing technique performs better than simple exponential smoothing technique in both conditions. Double exponential smoothing technique provides lower mean absolute deviation (MAD), which shows that this technique has lower forecast errors. The results, analysis, and implementation will now be described.

## 4.1 Analyzing the Results

### *4.1.1 Compare between simple exponential smoothing and double exponential smoothing with 18 months data*

In the previous chapter, implementation of the forecasting technique was first applied to 18 months data, in order to develop forecast model. The application of using the double exponential smoothing technique has lower forecast error than using the exponential smoothing technique. The results show in the table 4.1. Moreover, mean square error (MSE) and mean absolute percentage error (MAPE) were also used to measure forecast error. The comparison of 18 months data included historical data, simple exponential smoothing technique, and double exponential smoothing technique. Moreover, results of using both techniques applied optimal a and β value for comparison in measurement of forecast error for the 18 months data.

**Table 4.1: Measurement of forecast error for 18 months data**

| Quarter | Period | Month | Actual | Historical Data .1 | | | | Simple Exponential Smoothing Technique | | | | Double Exponential Smoothing T nique | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Demand | Error | MAD | WE | MAPE (%J | Error | MAD | MSS | MAPE (%) | Error | MAD | MSS | MAPE (%) |
| | 1 | Oct-09 | 35433 | -44404 | 44484 | 1978826256 | 125.54 | - | | . | | | | | |
| | | cc-C9 | 98625 | -41020 | 42752 | 1830733328 | 8337 | 63192 | 55192 | 3993228864 | 6407 | 63192 | 63192 | 3993228864 | 6497 |
| | 3 | Dec-09 | 95586 | | 59205 | 4048572919 | 8713 | 19109 | - 1 50 | 1179189409 | 4293 | 9894 | 36543 | 2045557167 | 3721 |
| | 4 | Jan-10 | 119484 | •16821 | 48609 | 3107166199 | 6939 | 30595 | 57652 | 1764819039 | 3656 | 20663 | 31249 | 1506018776 | 30.57 |
| 2 | 5 | Feb-10 | 121165 | 24005 | 43688 | 2600980964 | 59.48 | 12404 | 31325 | 1362080643 | 2998 | 240 | 23497 | 1129528465 | 22.98 |
| | 6 | Mar-10 | 178735 | 48777 | 44536 | 2564016759 | 54,11 | 61918 | 37444 | 1856420214 | 3011 | 50675 | 28933 | /417221394 | 24.05 |
| | 7 | Apr-10 | 145490 | 48364 | 45083 | 2531882435 | 51.13 | -11544 | 33127 | 1569226701 | 2798 | -29291 | 28992 | 1324013476 | 2347 |
| | | May-10 | 158546 | 32871 | 43557 | 2350459961 | 4733 | 9010 | 29682 | 1356648783 | 2492 | | 25289 | 1136214485 | 2D 33 |
| | 9 | Jun-10 | 189719 | 83862 | 48035 | 2870723859 | 46.98 | 34331 | 30263 | 1334394019 | 23.28 | 23650 | 25084 | 105410/026 | 1935 |
| | 10 | Jul-1C | 206135 | 17139 | 44945 | 2613026005 | 43.12 | 28448 | 30061 | 1276052095 | 22.23 | 15159 | 23981 | 971400326.8 | 18.02 |
| | 11 | | 273708 | 45984 | 45040 | 2567708028 | 40.72 | 77544 | 34810 | 1749750851 | 22.84 | 63089 | 27892 | 1272287955 | 18.52 |
| | 12 | | 200524 | 14248 | 42474 | 2370649484 | 37.92 | -46006 | 35827 | 1783096445 | 22.85 | -68523 | 31586 | 1583482204 | 19,94 |
| | 13 | | 257668 | 35727 | 41955 | 2286477872 | 56.07 | 41020 | 36260 | /774722031 | 22.27 | 30267 | 51476 | 1527865803 | 1926 |
| 1 | 14 | Nov-1C | 198605 | -26262 | 40834 | 2172421785 | 34.44 | -44686 | 36908 | 1791809510 | 22,29 | -59007 | 33594 | 1678166065 | 20.06 |
| | 5 | Dec-1C | 183060 | -44380 | 41070 | 2158899292 | 33.76 | •31207 | 36501 | 1733385251 | 21.91 | •35795 | 33751 | 1649819632 | 20.03 |
| | 16 | Jan-11 | 261967 | 5 363 | 42151 | 2236858072 | 33.04 | 67969 | 38599 | 1925815790 | 22.18 | 68962 | 36098 | 1856881415 | 20.45 |
| 2 | 17 | Feb-11 | 210635 | 28983 | 41376 | 2154 791 | 3191 | -27510 | 37906 | 1852751215 | 21.61 | -36652 | 36133 | 1824786428 | 20.26 |
| | 18 | Mar-11 | 253444 | 22341 | 40319 | 2062714651 | 30,63 | 33167 | 37627 | 1808475634 | 21,11 | 30089 | 35777 | 1770702969 | 19.76 |

Source: Author's own

Historical data has a mean absolute percentage error equal to 30.63%. Simple exponential smoothing has a lower mean absolute percentage error than historical data, which equals 21.11%. The difference of MAPE between historical data and simple exponential smoothing is 9.52%. Double exponential smoothing provides a lower MAPE than historical data and simple exponential smoothing, equal to 19.76%. Both techniques provide lower MAPE than historical data, which means that simple exponential smoothing and double exponential smoothing are both effective with 18 months data. The variance between simple exponential smoothing and double exponential smoothing technique is only a small difference, when compared with historical data, which equals 1.35%. However, the most appropriate forecasting technique for 18 months is the double exponential smoothing technique.

*4.1.2 Compare between simple and double exponential smoothing with 21 months data*

Double exponential smoothing is an appropriate forecasting technique for 18 months data. However, a model must be validated in order to prove that this technique will function with the SSD product. In Chapter III, the double exponential smoothing technique was tested, additional 3 months data was added in order to confirm that this technique could still be able to apply in the future. Table 4.2 shows the results of MAD, MSE, and MAPE using simple exponential smoothing technique and double exponential smoothing technique.

**Table 4.2: Measurement of forecast error for 21 months data**

| | | | Actual | | Historical Data | | | Simple Exponential Smoothing Technique | | | | Double Exponential Smoothing Technique | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quarter | Period | Month | Demand | Error · | MAD | MSE | MAPE (%) | Error | MAD | MSE | MAPE (%) | Error | MAD | MSE | MAPE (%) |
| 1 | | Oct-09 | 35433 | -44484 | 4414 | 1978826256 | 125.54 | • | | - | ˇ | | | | |
| | 2 | Nov-09 | 98625 | -41020 | 42752 | 1830733328 | 83.57 | 63192 | 63192 | 3993228864 | 64.07 | 715⁴3 | 71543 | 5118441882 | 72.54 |
| | 3 | Dec-09 | 95586 | -92110 | 59205 | 4048572919 | 87.83 | 17715 | 40454 | 2153527012 | 41.30 | 21765 | 41654 | 2628434235 | 42.42 |
| | 4 | inn-IC | 119484 | -16821 | 48569 | 3107166199 | 69.39 | 29716 | 36874 | 1730034797 | 35.83 | 20552 | 34620 | 1893082461 | 34.02 |
| | 5 | Feb-10 | 121165 | 24005 | 43688 | 2606980964 | 59.48 | 11441 | 30516 | 1330248284 | 29.29 | 0 | 25965 | 1419811846 | 25.51 |
| | 6 | Mar-1D | 178735 | 48777 | 44536 | 2564016759 | 54.11 | 61327 | 36678 | 1816409847 | 30,25 | 50147 | 30802 | 1638803516 | 26.02 |
| 3 | | Apr-1C | 1.45490 | 48364 | 45083 | 2531882435 | 51.13 | -13103 | 32749 | 1542290786 | 26.71 | -28512 | 30420 | 1501153920 | 24.95 |
| | 8 | May-10 | 158546 | 32871 | 43557 | 2350459961 | 47.33 | 8753 | 29321 | 1332907290 | 23.68 | -3341 | 26551 | 1288297693 | 22.69 |
| | 9 | Jun-11 | 189719 | 83862 | 48335 | 2870723859 | 46.98 | 34048 | 29912 | 1311198587 | 22,96 | 22803 | 26083 | 1192260378 | 20.48 |
| 4 | 10 | Jul-10 | 206135 | 17139 | 44945 | 2613026005 | 43.12 | 27598 | 29655 | 1250138977 | 21.90 | 14746 | 24823 | 1083948668 | 19,00 |
| | 11 | Aug-10 | 273731 | 45984 | 45040 | 2567708028 | 40,72 | 76637 | 34353 | 1712449116 | 22.51 | 63000 | 28641 | 1372448074 | 19.40 |
| | 12 | Sep-10 | 200524 | 14248 | 42474 | 2370649484 | 37.92 | -48014 | 35595 | 1766349828 | 22.64 | -66876 | 32117 | 1654260297 | 20.67 |
| - | 15 | Oct-11 | 257668 | 35727 | 41955 | 2286477872 | 36,07 | 41375 | 36077 | 1761809816 | 22.09 | 29570 | 31905 | 1589271683 | 19.90 |
| | 14 | Nov-10 | 198605 | | | 2172421785 | 34.44 | -45474 | 36799 | 1785356249 | 22.£5 | -594E6 | [illegible] 6 | 1739216787 | 20.68 |
| | 15 | Dec-10 | 183061 | | 41070 | 2158899292 | 33.76 | -30480 | 36348 | 1724190565 | 21.76 | -383 'C | 34384 | 1719981560 | 20.69 |
| 2 | 16 | Jan-11 | 261967 | 58363 | 42151 | 2236858072 | 33.04 | 68896 | 38518 | 1925692471 | 22.06 | 64949 | 36375 | 1886540128 | 20.97 |
| | 17 | Feb-11 | 210635 | 28983 | 41376 | 2154690791 | 31.91 | -28704 | 37905 | 1856833045 | 21,54 | -38496 | 36508 | 1861253027 | 20.8C |
| | 18 | Mar-11 | 253444 | 22341 | 40319 | 2062714651 | 30.63 | 33382 | 37639 | 1813156609 | 21.04 | 27604 | 35984 | 1796590125 | 20.22 |
| 3 | 19 | Apr-11 | 263390 | -68954 | 41826 | 2204395676 | 30.39 | 20910 | 36709 | 1735715000 | 20.32 | 12834 | 34698 | 1705930358 | 19.36 |
| | 20 | May-11 | 289433 | 36588 | 41564 | 2161109979 | 29.50 | 32910 | 36509 | 1702313565 | 19.84 | 24011 | 34136 | 1646487733 | 18.78 |
| | 21 | Jun-11 | 202829 | 45163 | 41736 | 2155328388 | 29.16 | -75999 | 38484 | 1905992493 | 20.73 | -86722 | 36765 | 1940196834 | 19.98 |

Source: Author's own

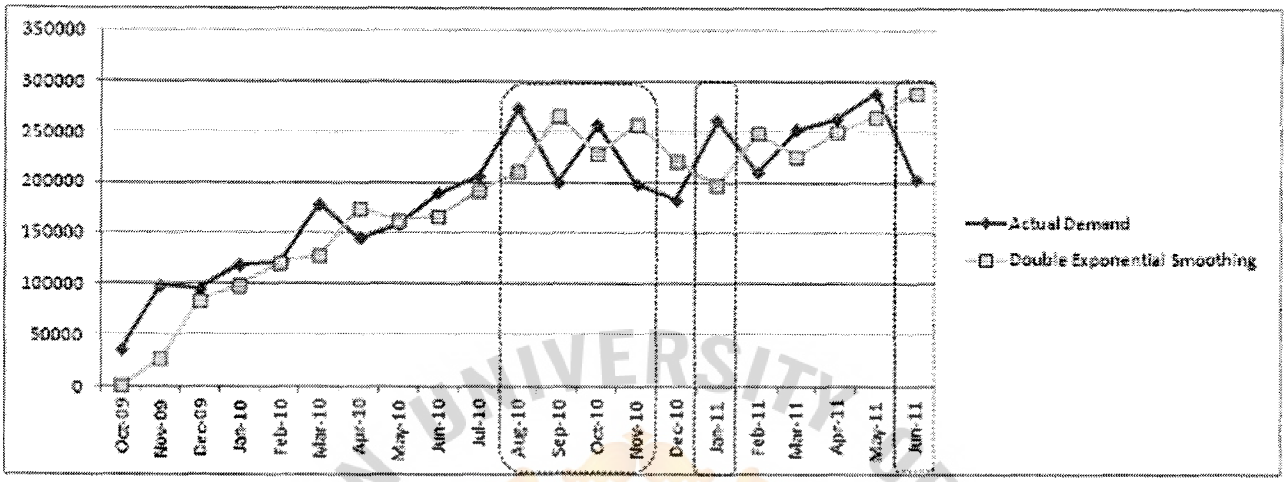
The results shows that double exponential smoothing technique still perform better than exponential smoothing technique. However, exponential smoothing technique provides better result for 21 months data, when compared with results from table 4.1. However, the variance between simple exponential smoothing and double exponential smoothing technique is only 0.75%.

### 4.2 Implementing the Results

*4.2.1 Application of double exponential smoothing technique*

According to the results, double exponential smoothing technique provides lower percentage of forecast error. Figure 4.1 shows the relation between actual demand and forecasting technique by using double exponential smoothing.

**Figure 4.1: Comparison between actual demand and double exponential smoothing technique**




Source: Author's own

Regarding the line graph, at the beginning of the SSD project, double exponential has a positive relationship with actual demand. However, demand fluctuation starts from August 2010 to November 2010, and double exponential smoothing is not able to follow the variation during that period. Similarity, January 2011 and June 2011 also faced demand fluctuation, and the double exponential forecasting model adjusted trend follows from past demand but a variation occurs during that period. The reason for the variation during August 2010 to November 2010 and January 2010 is because there are new end-customer groups starting to order from the company, and also some existing end customers switched to buying from other competitors. Moreover, the company faced problem about quality control with the SSD product, which had already shipped out during March 2011 to May 2011. Consequently, some end customers decrease their orders due to quality problem. Without uncontrollable factors like new end customers, outside competitors, and quality problems, the double exponential smoothing technique has a positive relationship with actual demand.

### 4.3 Evaluation of double exponential smoothing technique

The results of double exponential smoothing application, which excludes the identified uncontrollable factors, were accepted by the management team, because of the lower forecast errors. The application of double exponential smoothing technique provides a low percentage of forecast error, which can indicate that this application can reduce demand variation. Consequently, it can secure cost saving for the company, from carrying cost and additional production cost. Carrying cost occurs when the company needs to carry inventory caused by over production. Additional production cost occurs when a company faces shortage in trying to fulfill customer demand. Table 4.3 shows cost saving from the double exponential smoothing application.

**Table 4.3: Cost saving of double exponential smoothing application**

| | | | | | | | Historical dare | | | Double Exponential Smoothing Technique | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quarter | Period | | al Demand | Selling Price | Build | Error | Additional production cost (10% from selling price) | Carrying cost (90% from selling price) | Forecast | Error | Additional production cost (10.0% from selling price) | Carrying cost 90% from selling |
| | | | [illegible] | 30 5 | - | | | | | | | |
| | 2 | Nov-09 | 96625 | 30 5 | 139645 | [illegible] | | 1117548 | 27052 | 71543 | 214630 | |
| | 3 | Dec-09 | 95566 | 30 5 | 177E36 | | | 2 86970 | 83E21 | 12765 | 35298 | |
| | 4 | Jan 11 | 119484 | 30$ | 136305 | 15821) | | 454167 | 48932 | 28552 | 51E56 | |
| | | 908-10 | 121165 | 303 | 97260 | 24005 | 72015 | | 1211E5 | | | |
| | | Mar-10 | 173735 | 305 | 129958 | 46777 | 146331 | | 128568 | 54147 | 150442 | |
| | | Ap | 145490 | 30$ | 97126 | 49364 | 145092 | | 174002 | (28512) | | 759811 |
| | | May-10 | 1535⁴6 | 30 5 | 125675 | 32971 | 93613 | | 161387 | (3941) | | 90199 |
| | | Jun-10 | 199739 | 305 | 105857 | 83962 | 251586 | | 166916 | 22803 | 68410 | |
| | 10 | 141-10 | 208335 | 305 | 368995 | 17139 | 51417 | | 191389 | 14736 | 44239 | |
| | 11 | Aug-10 | 273702 | 30 5 | 227724 | 45954 | 137952 | | 210708 | 53338 | 188999 | |
| | 12 | Sep-10 | 203523 | | 186276 | 14242 | 42744 | | 26740:§ | (65879) | | 7$05945 |
| | 13 | Oct-10 | 257668 | 30 5 | 221941 | 55727 | 147151 | | 228098 | 19575 | 88711 | |
| | 14 | Nov-10 | 198605 | 305 | 224967 | (25262) | | 709074 | 258091 | (59485) | | 3645115 |
| | 15 | Dec-10 | 183060 | 305 | 227440 | 144338) | | 1198260 | 221440 | 138340) | | 1035169 |
| | 16 | Jan-11 | 261967 | 305 | 203604 | 58363 | 175089 | | 197018 | 6=743 | 194847 | |
| | 17 | Feb-11 | 210635 | 305 | 161652 | 28983 | 85949 | | 249131 | | | 1035394 |
| 2 | 18 | Mar-11 | 253444 | 10 5 | 231103 | 22341 | 67223 | | 225843 | 7 | 22312 | |
| | 29 | Apr-11 | 263390 | 305 | 332344 | (69954) | | 1861758 | 250556 | | 36502 | |
| | 27 | May-11 | 288433 | 305 | 252845 | 36588 | 189764 | | 255322 | 1 | 72033 | |
| 3 | 21 | Jun-11 | 202529 | 30 $ | 247992 | 1⁴5153i | | 1213401 | 2893 7 | (86722) | | 2341488 |
| | | | | | | | 1491755 | 10238238 | | | 1240577 | 8687825 |
| | | | | | | TOTAL COST | 11729994 | | | TOTAL COST | 9928402 | |

Source: Author's own

According to historical data, the company has an additional production cost of 1,491,756 U.S. dollars. After applying the double exponential smoothing technique, the additional production cost is 1,240,577 U.S. dollars, so the company can save 251,179 U.S. dollars. Moreover, the company can also save carrying cost, which the historical data shows as 10,238,238 U.S. dollars. Applying double exponential smoothing technique enables the cost to reduce to 8,687,825 U.S. dollars, meaning that the company can save 1,550,413 U.S. dollars.

Therefore, application of the double exponential smoothing technique helps the company to save both additional production cost and carrying cost, equal to 1,801,592 U.S. dollars.

**4.4 Managerial perspectives**

The double exponential smoothing forecast technique was accepted by the top management team. The forecasting technique does not require any additional cost, as the company can use existing resources. The technique can help the company to reduce additional production cost and inventory carrying cost. On the other hand, collaboration between the factory and sales department is required in sharing information from customers. That will help the company to have more accurate forecasting.

# CHAPTER V

# SUMMARY FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

Now at the completion of this graduate research project, the findings and conclusions with theoretical and managerial implications will be summarized here. In addition, limitations and suggestions for future research are described.

## 5.1 Summary of the Findings

The purpose of this graduate project has focused on developing a suitable forecasting model for SSD manufacturing. There has been no systematic forecasting in the company. The management team wanted to create systematic forecasting for the SSD project. Furthermore, the company is facing end-customer demands fluctuations, which cause variations between build request quantity and actual demand. Efficiency of SSD production has low efficiency, due to over production causing excess inventory, and over-time production in order to cover shortage due to demand fluctuation.

Historical data was collected which started from October 2009 to March 2011, in order to define demand patterns. It was revealed that the data shows a horizontal pattern in the beginning period and slightly increases with a trend pattern. Theoretically, time series forecasting is suitable for demand with horizontal and trend pattern. Many citations describe that exponential smoothing techniques are effective forecasting techniques when compared with other techniques. The case study selected two techniques from exponential smoothing techniques, which are simple exponential smoothing technique and double exponential smoothing technique.

## 5.2 Conclusions

Applications of simple exponential smoothing technique show lower MAD than historical data. However, double exponential smoothing can provides better results, because it has lower MAD for 18 months data. Moreover, model validation was performed in order to confirm that double exponential smoothing is suitable for use with the SSD product. The case study used 21 months data for testing double exponential smoothing technique. The results of testing with 21 months data showed that double exponential smoothing still performs better than simple exponential smoothing.

## 5.3 Theoretical Implications

Simple exponential smoothing and double exponential smoothing have different optimal a and 13 value when comparing results between 18 periods and 21 periods. It relates with the theory of exponential smoothing that smoothing constant and trend adjustment can be any value between 0-1.

Double exponential smoothing technique performs better than simple exponential smoothing technique because double exponential smoothing technique has both a and $\beta$ values, and $\beta$ value can adjust forecast value by including trend components from actual demand. In contrast, simple exponential smoothing has only **a** value, which is only a smoothing forecast value without any trend components adjustment.

## 5.4 Managerial Implications

The result of using double exponential smoothing technique shows that it can provide lower percentage of error, as measured by MAPE. From a management team perspective, applying double exponential smoothing technique can help the company to achieve cost savings. The company can reduce both additional production cost and carrying cost. The total cost saving is 1,801,592 U.S. dollars. The management team is satisfied with the result because this technique can save cost without needing investment, as the company can uses existing resources such as Microsoft Excel.

### 5.5 Limitations and Recommendations for Future Research

The implementation of double exponential smoothing technique can accomplish the research objectives in this graduate project. However, this forecasting technique still has some forecast errors. The case study applies only two techniques from exponential smoothing forecasting. The other techniques, in time series forecasting, should be applied in future research. Moreover, causal methods and other sophisticated techniques, for example, artificial intelligence, could be considered as an alternative for future studies. Internal collaboration between the sales department and factory is also an important factor for improving forecasting accuracy by sharing information. Furthermore, collaborative forecasting planning and the replenishment (CPFR) model could be applied for collaborative forecasting between a company and its customers in order to share forecast information and cooperate in developing the most appropriate and effective forecasting model.

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# APPENDICES

# APPENDIX A

Simple Exponential Smoothing by SOLVER

**Figure 1: Simple Exponential Smoothing Microsoft Excel SOLVER Parameter Settings**

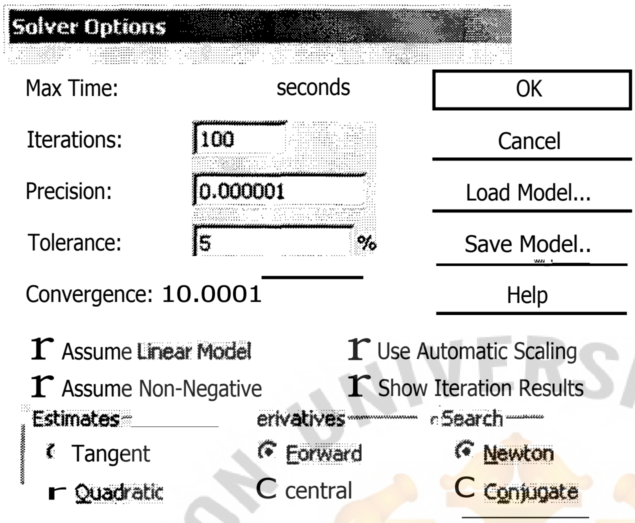
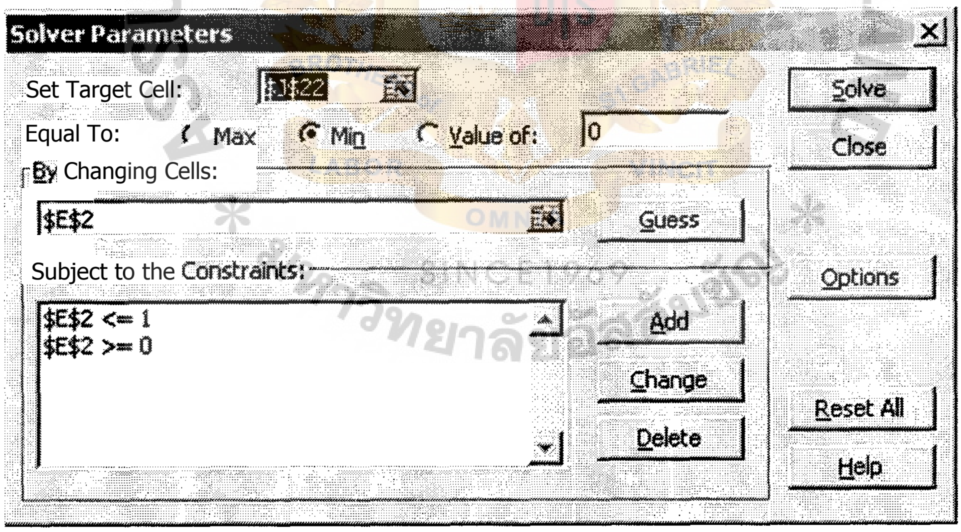



**Figure 2: Determine Target and Constraint of Simple Exponential Smoothing in SOLVER**



### Figure 3: Answer Report of Simple Exponential Smoothing from SOLVER

**Microsoft Excel 12.0 Answer Report**
**Worksheet: (Exponential smoothing.xls]Alpha 0.9**
**Report Created: 2012101131 10:57:45 PM**

Target Cell (Min

| Cell | Ori 'nal Value | Final Value |
|---|---|---|
| | | 37627 |

Adjustable Cells

| Cell | Name | Original Value | Final Value |
|---|---|---|---|
| $E$2 | Al h a | | 0.649514223 |

| | | | | |
|---|---|---|---|---|
| $E$2 | Alpha a | 0.649514223 | $E$2<=1 | ..350485777 |
| $E$2 | Alpha a | 0.649514223 | $E$2>=0 | 0,649514223 |

### Figure 4: Sensitivity Report of Simple Exponential Smoothing from SOLVER

Microsoft Excel 12.0 Sensitivity Report
Worksheet: [Exponential smoothing.xls]Alpha 0.9
Report Created: 2012/01/31 10:57:46 PM

Adiustable Cells

| Cell | Name | inal Value | Reduced Gradient |
|---|---|---|---|
| $E$2 | Alpha a | 0649514223 | 0 |

Constraints
NONE

### Figure 5: Limits Report of Simple Exponential Smoothing from SOLVER

Microsoft Excel 12.0 Limits Report
Worksheet: (Exponential smoothing.xls]Limits Report 1
Report Created: 2012/01/31 10:57:46 **PM**

| Cell | Target Name | Value |
|---|---|---|
| $J$22 | MAD | 37627 |

| Cell | Adjustable Name | Value | Lower Limit | Target Result | Upper Limit | Target Result |
|---|---|---|---|---|---|---|
| $E$2 | Alpha α | 0.649514223 | 0 | 150043.2353 | 1 | 40519.23529 |

APPENDIX B

Double Exponential Smoothing by SOLVER

**Figure 1: Double Exponential Smoothing Microsoft Excel SOLVER Parameter Settings**

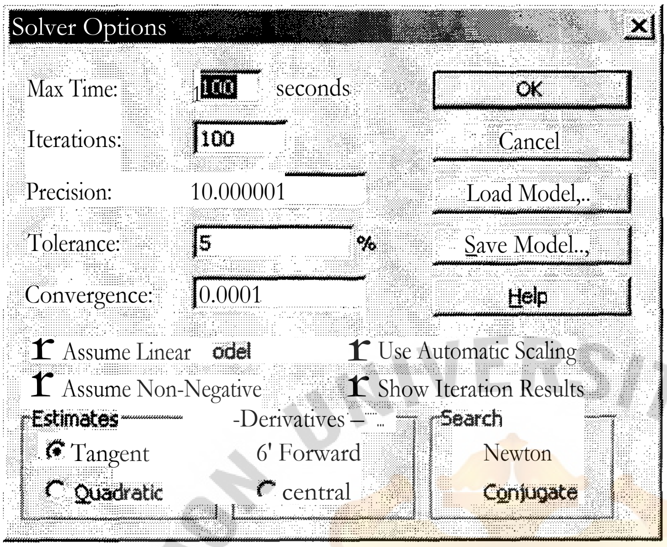



**Figure 2: Determine Target and Constraint of Double Exponential Smoothing in SOLVER**

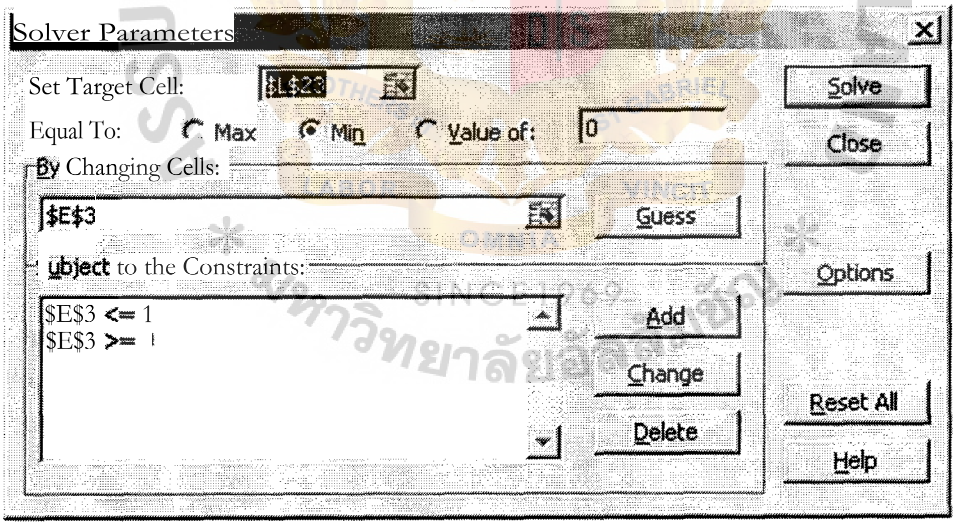


**Figure 3: Answer Report of Double Exponential Smoothing from SOLVER**

Microsoft Excel 12.0 Answer Report
Worksheet (Double Exponential smoothing.xls]Optimal period 18
Report Created: 2012/01/31 11:16:53 PM

| Call | Name | Original Value | Final Value |
|---|---|---|---|
| $L523 | MAD | 35829 | 35777 |

Adiustable Cells

| Cell | Name | Original Value | Final Value |
|---|---|---|---|
| $E$3 | Beta 3 | 0.157044948 | 0.224519188 |

nstraints

| Cell | Name | Cell Value | Formula | Status | Slack |
|---|---|---|---|---|---|
| $E$3 | Beta β | 0.224519188 | $E$3<=1 | Not Binding | 0.775480812 |
| $E$3 | Beta | 0.224519188 | $E53>=0 | Not Bindinc | 0.224519188 |

**Figure 4: Sensitivity Report of Double Exponential Smoothing from SOLVER**

Microsoft Excel 12.0 Sensitivity Report
Worksheet: [Double Exponential smoothing.xls]Optimal period 18
Report Created: 2012/01/31 11:16:53 PM

Adiustable ells

| C | me | Final Value | Reduced Gradient |
|---|---|---|---|
| SE$3 | Beta β | 0.2245191 | 0 |

Constraints
NONE

**Figure 5: Limits Report of Double Exponential Smoothing from SOLVER**

Microsoft Excel 12.0 Limits Report
Worksheet: [Double Exponential smoothing.xls]Limits Report 1
Report Created: 2012/01/31 11:16:53 PM

| Cell | Name | Target Value |
|---|---|---|
| $L$23 | MAD | 3 777 |

| Cell | Name | Adjustable Value | Lower Limit | Target Result | Upper Limit | Target Result |
|---|---|---|---|---|---|---|
| $E53 | Beta p | 0.224519186 | 0 | 37627.06669 | 1 | 4578140475 |