# A Comparative Study of Load Forecasting Using Moving Average, Exponential Smoothing and ARIMA Model

by

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Dissertation submitted in partial fulfilment of

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the
Electrical and Electronics Engineering Programme
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in partial fulfilment of the requirement for the
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Approved by,

(Samsul Ariffin bin Abdul Karim)

UNIVERSITI TEKNOLOGI PETRONAS
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## CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

SAIFUL AZLI BIN SUHAIMI @ ALWI

# ABSTRACT

Load electricity forecast has been a central and an integral process in the planning and operation of electric utilities. Many techniques and approaches have been investigated to tackle this problem in the last two decades. These are often different in nature and apply different engineering considerations and economic analyses. For this project, the main focus direct to Gas District Cooling Plant (GDC) which acts as primary source of energy in Universiti Teknologi PETRONAS (UTP). The project will use raw data to obtain weekly forecast using time series method which are moving average and exponential smoothing techniques. The forecast will be very important to obtain best accurate model to support plant operation as UTP is the prolific higher education centre and very much dependent on itself. The model will be simulated and designed using MATLAB software and certain parameters will be evaluated to diagnose the performance. The error percentage also will be calculated. The least value of error obtained will be the best forecast accuracy of this project. The proposal consists of an introduction, problem statement, objectives, literature review and methodology of the research. Then it is further described with results and discussion.

# ACKNOWLEDGEMENT

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# CHAPTER 1

# INTRODUCTION

## 1.1 Background of Study

The dramatic growths in the entities that need to be forecast by multinational organizations have made demand forecasting methods and systems larger in scale. The term forecast often is used far too loosely in most companies. For example, there is sales department forecast, a marketing department forecast, a financial department forecast and plan (budget), an operation forecast, and a demand forecast. In reality, there is only one unconstrained demand that predicts the unlimited demand for a company's product. From that unconstrained demand forecast we create a constrained plan, not a forecast, by matching supply, requiring companies either to lower their unconstrained demand forecast or to incur additional costs to increase supply [9].

Forecast model will be designed using moving average techniques and exponential smoothing which will be able to determine the suitable time for plant operation in Universiti Teknologi PETRONAS throughout the whole year of operation. The proposed model will be introduced by different these techniques with the load data as input while the output would be future load data. The accuracy of the data will be determined by calculating mean absolute percentage error (MAPE).

## 1.2 Problem Statement

### 1.2.1 Problem Identification

There is an urgent need for precision in the demand forecasts. In the past, the world over, an underestimate was usually attended to by setting up turbine generator plants fired by cheap oil or gas, since they could be set up in a short period of time with relatively small investment [6]. On the other hand, overestimates were corrected by demand growth

The presence of economies of scale, lesser focus on environmental concerns, predictability of regulation and a favourable public image, all made the process of forecasting demand much simpler. In contrast, today an underestimate could lead to under capacity, which would result in poor quality of service including localized brownouts, or even blackouts. An overestimate could lead to the authorization of a plant that may not be needed for several years [9].

Moreover, in view of the ongoing reform process, with associated unbundling of electricity supply services, tariff reforms and rising role of the private sector, a realistic assessment of demand assumes ever-greater importance. These are required not merely for ensuring optimal phasing of investments, a long term consideration, but also rationalizing pricing structures and designing demand side management programs, which are in the nature of short- or medium-term needs [6].

### 1.2.2 Significance of Project

In manufacturing institutions and electric utilities there are a number of factors that drive the forecast, including market share. The forecast further drives various plans and decisions on investment, construction and conservation. Since electric utilities are basically dedicated to the objective of serving consumer demands, in general the consumer can place a reasonable demand on the system in terms of quantity of power [6].

Specifically, for UTP, by modelling a prediction model using moving average and exponential smoothing techniques, it will help to improve the current electricity management by GDC UTP in terms of scheduling the plant and maintenance and as the part to support plan operation.

Figure 1 : Gas District Cooling Plant in UTP

Figure 2: Gas Turbine during Maintenance

## 1.3 Objective and Scope of the Project

### 1.3.1 Main Objective

To determine the performance of electricity forecasting model by using moving average and exponential smoothing techniques which will be developed using z-transform. The accuracy of the both model will be measured and compared using error measurement which Mean Absolute Percentage Error (MAPE).

### 1.3.2 Scope of Project

The project will start will collecting some journals related to the research to gather information of the literature review and theory of the forecast. Next is the data gathering from GDC UTP. The data will be transformed to model and will be simulated using MATLAB software. The data usually will predict based on one week prediction. Further analysis will be carried out to obtain the most accurate forecast model.

## 1.4 Relevancy of the Project

A precise estimate of demand is important for the purpose of setting tariffs. A detailed consumer category-wise consumption forecast helps in the determination of a just and reasonable tariff structure. The nature of the forecasts has also changed over the years. It is not enough to just predict the peak demand and the total energy use, say on an annual basis.

The forecast plays an important role in identifying the categories which "can pay" and those that should be subsidized. Moreover, the accuracy of the model predicted will ensure the longevity and continuous supply to the consumer itself.

## 1.5 Feasibility of Project

The project will be carried out in two semesters which will be based on three important areas. They are research, development and improvement of the model. The objective is to obtain the best model possible to forecast electricity consumption in UTP based on data obtained from GDC. MATLAB software will be used as the tools to develop the algorithm of the techniques. System testing and implementation also will be done using this software.

# CHAPTER 2
# LITERATURE REVIEW

## 2.1 The Importance of Load Forecasting

Decision making in energy sector has to be based on accurate forecasts of the load demand [2]. The deregulation of energy markets has increased the need for accurate forecasts even more. Various classes of load forecasting models have been suggested as reported in. Almost all conventional short term load forecasting methods fall into the class of time series or regression approaches, which have the possibility of numerical instability due to improper modelling of the stochastic factors of the load [3]. For this project we mainly focus on the moving average technique, naive forecasting and exponential smoothing. The assumption of all these techniques is that the activities responsible for influencing the past will continue to impact the future [9].

The assumption with most statistical forecasting methods is that the farther out attempt to forecast, the less certain should be of the forecast. The stability of the environment is the key factor in determining whether trend, cycle, and seasonal extrapolations are appropriate forecasting methods. The study of the historical data, known as exploratory data analysis, identifies the trends, cycles and seasonality as well as other factors in the data so that appropriate models can be selected and applied [9].

The most common mathematical models involve various forms of weighted smoothing methods. Another type of model is known as decomposition. This technique mathematically separates the historical data into trend, cycle, seasonal, and irregular (or random) components [9].

## 2.2 Short Term Load Forecasting – Time Series Approach

For short term electricity forecasting, it plays an important role in power system operation and planning obviously. Accurate forecasting and prediction can saves costs by improving economic load dispatching. On the other hand it enhances the function of security control. It has now become one of the major fields of research in electrical engineering [6] [12].

Short-term load forecasts (STLF) usually aim to predict the load up to one-week ahead [7]. One of the drawbacks of these models is the inability to accurately represent the nonlinear relationship between load and temperature [1]. Load forecasting is an integral part of electric power system operations. Long lead time forecasts of 5 to 20 years ahead are needed for scheduling construction of new generating capacity as well as the determination of prices and regulatory policy. Intermediate term forecasts of a few months to 5 years ahead are needed for maintenance scheduling, coordination of power sharing arrangements and setting of prices, so that demand can be met with fixed capacity [4]. Short term forecasts of a few hours to a few weeks ahead are needed for economic scheduling of generating capacity, scheduling of fuel purchases, security analysis and short term maintenance scheduling. Very short term forecasts of a few minutes to an hour ahead are needed for real-time control and real time security evaluation [9].

The primary application of the STLF function is to drive the scheduling functions that determine the most economic commitment of generation sources consistent with reliability requirements, operational constraints and policies and physical, environmental, and equipment limitations. A second application of STLF is for predictive assessment of the power system security. The third application of STLF is to provide dispatchers with timely information [8].

Some sort of predictability may be possible in the short run and this may be sufficient for adaptive systems interacting with an external environment. Short-term predictability will embody the new information as it arrives at each new time step. Given a certain number of elements of a time series the next element will be forecasted [13].

One of the disadvantages of the Box and Jenkins transfer function model is that, because it is a linear model, it does not accurately reflect the load/temperature relationship. Hagan and Klein were able to circumvent this problem somewhat by continuously updating the model parameters, which effectively relinearized the model after each measurement. In this paper a further improvement is gained by subjecting the temperature to a nonlinear transformation before using it in the transfer function model [4].

Box and Jenkins time series models (ARIMA, Periodic ARIMA and Transfer Function) are very well suited to load forecasting applications. They have been used for long term forecasts of more than a year ahead, as well as for very short term forecasts of less than five minutes. One of the drawbacks of these models for short term forecasts is their inability to accurately describe the nonlinear relationship between loads and temperatures. The paper has demonstrated that a simple polynomial regression analysis, when combined with a Box and Jenkins transfer function model, can provide more accurate forecasts. Up to now, the main focus in load forecasting has been on STLF since it is an important tool in the day-to-day operation of utility systems.

This nonlinear model has been compared with the standard transfer function model, the periodic ARIMA model and with a utility procedure which uses heavy dispatcher input. All of the Box and Jenkins models provide accurate forecasts, but the simple nonlinear extension to the transfer function model provides the best results. These results suggest that continued development of the nonlinear model of the load/temperature relationship should provide further improvements in short term load forecasts [4].

The load demand is influenced by numerous factors – ranging from weather conditions over seasonal effects to socio-economic factors. The demand is high on cold days which can be attributed to electric heating. Similarly, in hot days, the increased usage of air conditioning generates a higher demand of energy [7].

## 2.3 Medium-Term Load Forecasts and Long-Term Load Forecasts

Medium-term load forecasts usually incorporate several additional influences – especially demographic and economic factors. In the case of long-term load forecasts, even more indicators for the demographic and economic development have to be taken into account. The time series of the loads itself has generally three seasonal cycles; an intra-daily cycle (the daily load curve or the load profile), a weekly cycle, and yearly seasonal cycle. Many of them are developed for STLF although MTLF has gained importance which is especially due to the deregulation of electricity markets [7].

## 2.4 Neural Network

Neural network can perform intelligent mathematical operations. It consists of several layers of neurons, which are named after human brain cells. The first layer is the input neurons, which are the input data. The hidden neurons learn how to combine the inputs to produce the desired results. The output neurons present the results.

A neural network is trained by repeatedly presenting examples that include both inputs and outputs. The network learns from each example and calculates an output. If the output does not agree with the target output, the network will be corrected by changing its internal connections. Some connections will be strengthened and others weakened. This training will be continued until the network reaches a desired level of accuracy.

One problem with neural networks is that there are many numeric parameters that can be chosen as input data. Quite a number of these parameters, especially indicators, are slight variations of each other, and therefore redundant. They employ the methods of evolution, and especially the principle of the survival of the fittest. The less fit parameter will die, and the best fit parameter will be selectively bred.

## 2.5 Moving Averaging

A range of smoothing techniques can be deployed, including simple moving averaging, double moving averaging, and centre moving averaging [9]. Moving averaging techniques provide a simple method for smoothing past demand history. These decomposition components are the basic underlying foundation of almost all time series methods.

The principle behind moving averaging is that demand observations (weekly/monthly periods) that are close to one another are also likely to be similar in value. So, taking the average nearby historical periods will provide good estimates of trend, cycle for that particular period. The result is a smoothed trend/cycle component that has eliminated some of the randomness. The moving average procedure creates a new average as each new observation (or actual demand) becomes available by dropping the oldest actual demand period and including the newest actual demand period. The key to moving averaging is determining how many periods to include [9].

Choosing the inappropriate smoothing length can have dramatic effects on predictions. The standard rule of thumb is that the larger the number of periods in the moving average, the more randomness is removed from the trend/cycle component. However, it also means the trend/cycle component is more smoothed and not picking critical fluctuations in the demand history. It also requires a longer demand history, which may not be available. In other words, the longer the length of the moving average, the more terms and information may be lost in the process of averaging [9].

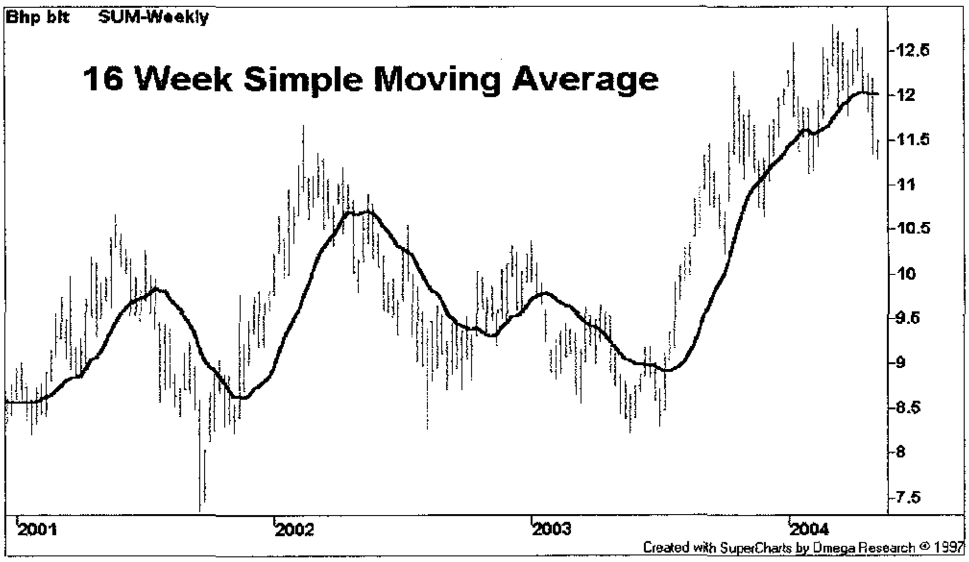



Figure 3: Example of 16 Week Simple Moving Average [17]

Table 1: Example of Moving Average Technique

| Days | Actual Load Data (kWatt) | 2 Days Moving Average Forecast Data (kWatt) |
|---|---|---|
| 1 | 4988 | - |
| 2 | 5112 | - |
| 3 | 5064 | (4988 + 5112) /2 = 5050 |
| 4 | 5060 | (5112 + 5064) /2 = 5088 |
| 5 | 3372 | (5064 + 5060) /2 = 5062 |
| 6 | 3184 | (5060 + 3372) /2 = 4216 |
| 7 | 2828 | (3372 + 3184) /2 = 3278 |

## 2.6 Naive forecast

A moving average of order 1, MA (1), where the last known demand point is taken as the forecast for the next demand period is an example showing that the last week's demand will be the same as next week's demand. This is also known as the naive forecast, as it assumes the current period will be the same as the next period [9]. The forecast analyst or planner must be pretty naive to think that the last week's demand will be the same as last week's demand. We should use the naive forecast as the benchmark when comparing other quantitative methods.

The main issue with moving averaging is that it can forecast accurately only one or two periods ahead. It tends to smooth the forecasts by removing fluctuations in demand that may be important (i.e., sales promotion, marketing event, or economic activities). As a result, this quantitative method is not used very often; methods of exponential smoothing are generally superior to moving averaging. Finally, if there is a sudden shift in demand, the moving average is unable to catch up to the change in a reasonable amount of time [9].


Figure 4: Example Graph of Naive Forecast [18]

### 2.7 Exponential Smoothing

In time series forecasting, there is random error using a structured process that assumes the mean (or average) is useful statistic that can be used to forecast future demand. However in many cases, the time series data contain an upward or downward trend or seasonal effects associated with time of the year, and other factors. When trend and seasonal effects are strong in the demand history of a product, moving averaging is no longer useful in capturing patterns in the data set [9].

Exponential smoothing as a method of automatic forecasting has been recommended and used in many applications. One facet of the exponential smoothing methodology is the ease of responding to changes in the pattern of time series (e.g.: demand) being forecast by temporarily increasing the appropriate smoothing parameter [15].

. A variety of smoothing methods were created to address this problem and improve on the moving averaging methods to predict the next demand period. Those methods are known as exponential smoothing models, and they require that particular parameter values be defined and adjusted using a range from 0 to 1 to determine the weights to be applied to past demand history [9].

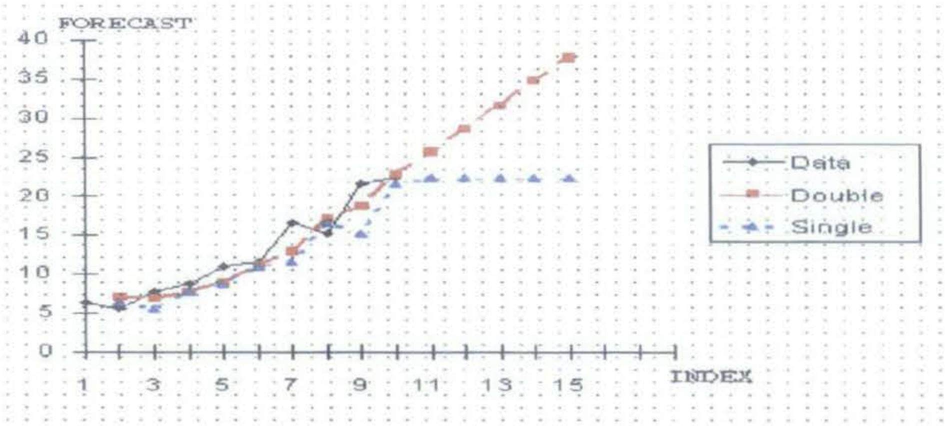



Figure 5: Single and Double Exponential Smoothing Graph [19].

Table 2: Example of Exponential Smoothing Technique

| Days | Actual Load Data (kW) | Exponential Smoothing (α = 0.5) |
|---|---|---|
| 1 | 4988 | 4256 |
| 2 | 5112 | 4256 + 0.5 (4988-4256) = 4622 |
| 3 | 5064 | 4622 + 0.5 (5112-4622) = 4867 |
| 4 | 5060 | 4867 + 0.5 (5064-4867) = 4965.5 |
| 5 | 3372 | 4965.5 + 0.5 (5060-4965.5) = 5012.8 |
| 6 | 3184 | 5012.8 + 0.5 (3372-5012.8) = 4192.4 |
| 7 | 2828 | 4192.4 + 0.5 (3184-4192.4) = 3688.2 |

### 2.7.1 Single Exponential Smoothing

The most practical extension to the moving average method is using weighted moving average to forecast future demand. The simple moving average method discussed so far in this chapter uses a mean (or average) of the past k observations to create a future one-period-ahead forecast. It implies that there are equal weights for all the k data points. The future demand forecasts are denoted as $F_t$. When a new actual demand period is observed, $Y_t$ becomes available, allowing to measure the forecast error, which is $Y_t - F_t$.

The single exponential smoothing (SES) method essentially takes the forecast for the previous demand period and adjusts it using forecast error. Then it makes the next forecast period [9].

$$F_{t+1} = F_t + \alpha(Y_t - F_{t)}$$

where $\alpha$ = constant between 0 and 1

Each new forecast is simply the old forecast plus an adjustment for the error that occurred from the last forecast. An $\alpha$ close to 1 will have an adjustment value is substantial, making the forecast more sensitive to swings in past historical demand based on the previous period's error. The closer the $\alpha$ value is to 1, the more reactive future forecast will be, based on past demand. When the $\alpha$ value is close to 0, the forecast will include very little adjustment, making it less sensitive to past swings in demand. In this case, the future forecasts will be much smoothed, not reflecting any prior swings in demand. These forecasts will always trail any trend or changes in past demand, since this method can adjust the next forecast based only on some percentage of change and the most recent error observed from the prior demand period.

In order to adjust for this deficiency associated with sample method, there needs to be a process that allows the past error to be used to correct the next forecast in the opposite direction. This has to be a self-correcting that uses the same principles as an automatic pilot in an airplane, adjusting the error until it is corrected, or we have equilibrium. With this approach, we can rewrite the equation as:

$$F_{t+1} = \alpha Y_t + (1 - \alpha) F_t = \alpha Y_t + \alpha(1-\alpha)Y_{t-1} + (1-\alpha)^2 F_{t-1}$$

In other words, $F_{t+1}$ is actually a moving average of all past demand periods, which can be described as $\alpha$ = 0.2, 0.4, 0.6, 0.8, or any number between 0 and 1 [9].

The literature includes descriptions of at least three methods: (1) "state-estimation" techniques, 2-3,8, (2) method of spectral expansion,1 and (3) load-weather linear regression models. In addition to forecast accuracy, the following considerations are also important: (1) the computer storage required, (2) the computer time required, and (3) the load and/or weather data required. To fully appreciate the generality of the method, it is important to note that the preceding assumptions are not usually restrictive. Any linear combination of common analytical functions of time, including constants, polynomials, exponentials and sinusoids can easily be written in the transition matrix form [1], [13].

The objectives of the analysis of load data are to select fitting functions and to suggest reasonable values for the smoothing constant [13], [3]. The approach for the data analysis was based on three preliminary assumptions:

- There is an annual growth of approximately seven percent.
- There are distinct seasonal variations.
- There is a distinct weekly pattern.

The forecasting technique developed in this paper provides the following features:

- Output - The method provides the capability for computing forecasts of hourly MWH load with lead times of one hour to one week. Standard errors for lead times of 1 to 24 hours range from two to four percent of average load. The forecast errors are normally distributed.
- Input - The forecasts are based solely on past values of observed load, measured in hourly MWH.
- Method - The forecast model adapts automatically to seasonal changes and changes in daily fluctuations. The method is also operationally simple. An hourly matrix multiplication and a vector addition are required to update the model. Computer storage requirements are reasonable, and operation of the system is continuous (throughout weekdays and weekends).

It is recognized that the development of the model and the operating experience described are based on two years of load data from only the AEP System. It is felt, however, that the demand patterns on the AEP System are statistically similar to those in other areas. Consequently, the forecasting technique and model should be generally applicable [13].

## 2.8 Autoregressive Integrated Moving Average (ARIMA)

The formula for ARIMA model is given as follow:

$$\alpha_p(B)\ (1\text{-}B)^d\ Y_t = \beta_q(B)\ Z_t$$

Here $\alpha_p(B)$ is the autoregressive component, $\beta_q(B)$ is the moving average component and $(1\text{-}B)^d$ the differencing component. Commonly the value of p, d, and q are determined by using autocorrelation function (ACF), partial autocorrelation function (PACF), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Box and Jenkins (1970) also suggested a four steps systematic procedure to attain the best value of p, d, and q which consists of model identification, model estimation, model validation and model application or forecasting.

The general model introduced by Box and Jenkins (1976) includes autoregressive as well as moving average parameters, and explicitly includes differencing in the formulation of the model. Specifically, the three types of parameters in the model are: the autoregressive parameters (*p*), the number of differencing passes (*d*), and moving average parameters (*q*). In the notation introduced by Box and Jenkins, models are summarized as ARIMA (*p, d, q*); so, for example, a model described as (0, 1, 2) means that it contains 0 (zero) autoregressive (*p*) parameters and 2 moving average (*q*) parameters which were computed for the series after it was differenced once.

### 2.8.1 Identification

As mentioned earlier, the input series for ARIMA needs to be stationary, that is, it should have a constant mean, variance, and autocorrelation through time. Therefore, usually the series first needs to be differenced until it is stationary (this also often requires log transforming the data to stabilize the variance). The number of times the series needs to be differenced to achieve stationary is reflected in the *d* parameter (see the previous paragraph). In order to determine the necessary level of differencing, you should examine the plot of the data and autocorrelogram.

Significant changes in level (strong upward or downward changes) usually require first order non seasonal (lag=1) differencing; strong changes of slope usually require second order non seasonal differencing. Seasonal patterns require respective seasonal differencing. If the estimated autocorrelation coefficients decline slowly at longer lags, first order differencing is usually needed. However, you should keep in mind that some time series may require little or no differencing, and that over differenced series produce less stable coefficient estimates.

At this stage we also need to decide how many autoregressive ($p$) and moving average ($q$) parameters are necessary to yield an effective but still *parsimonious* model of the process (*parsimonious* means that it has the fewest parameters and greatest number of degrees of freedom among all models that fit the data). In practice, the numbers of the $p$ or $q$ parameters very rarely need to be greater than 2.

### 2.8.2 Estimation and Forecasting

At the next step, the parameters are estimated using function minimization procedures, for more information on minimization procedures, so that the sum of squared residuals is minimized. The estimates of the parameters are used in the last stage to calculate new values of the series (beyond those included in the input data set) and confidence intervals for those predicted values. The estimation process is performed on transformed (differenced) data; before the forecasts are generated, the series needs to be integrated (integration is the inverse of differencing) so that the forecasts are expressed in values compatible with the input data. This automatic integration feature is represented by the letter I in the name of the methodology (ARIMA = Auto-Regressive Integrated Moving Average).

### 2.8.3 The constant in ARIMA models

In addition to the standard autoregressive and moving average parameters, ARIMA models may also include a constant, as described above. The interpretation of a (statistically significant) constant depends on the model that is fit. Specifically, (1) if there are no autoregressive parameters in the model, then the expected value of the constant is $\mu$, the mean of the series; (2) if there are autoregressive parameters in the series, then the constant represents the intercept. If the series is differenced, then the constant represents the mean or intercept of the differenced series; For example, if the series is differenced once, and there are no autoregressive parameters in the model, then the constant represents the mean of the differenced series, and therefore the linear trend slope of the un-differenced series.

# CHAPTER 3
# METHODOLOGY

## 3.1 Research Methodology

When it comes to quantitative methods, it is not difficult to predict or forecast the continuation of an established pattern or relationship. The difficulty is forecasting change related to a specific pattern or relationship, the timing of the change, and the magnitude of the change. This is the real test of a forecasting method and/or process. Although both quantitative and judgement methods operate based on the principles of identifying existing patterns and relationships, the real difference lies in the method by which information is captured, prepared and processed. Quantitative methods require system to access, store, and synchronize information (data). Then, using mathematical equations, we identify and model those patterns and relationships.

Most forecasting methods fall into two broad categories;

1. Those that rely on the subjective assessments of a person or group of persons are known as qualitative (also known as subjective or judgement) methods.
2. Those that rely on past sales history alone or built on a relationship between past sales and some other variable(s) are known as quantitative (also known as mathematical or objective) methods.

For this project, the literature review as well as brief research about the topic is carried out on several resources such as books, journals and also internet. For the purpose of reliability and performance, the forecasts model will be developed based on Semester OFF and Semester ON of UTP Academic Calendar.

Apart from that, the z-transform will be adapt as useful tool in the analysis of discrete-time signals and systems and is the discrete-time counterpart of the Laplace transform for continuous-time signals and systems [16]. The z-transform may be used to solve constant coefficient difference equations, evaluate the response of a linear time-invariant system to a given input, and design linear filters which will be used in MATLAB.

### 3.2 Flow Chart

The following flow chart explains the methodology in executing the project:

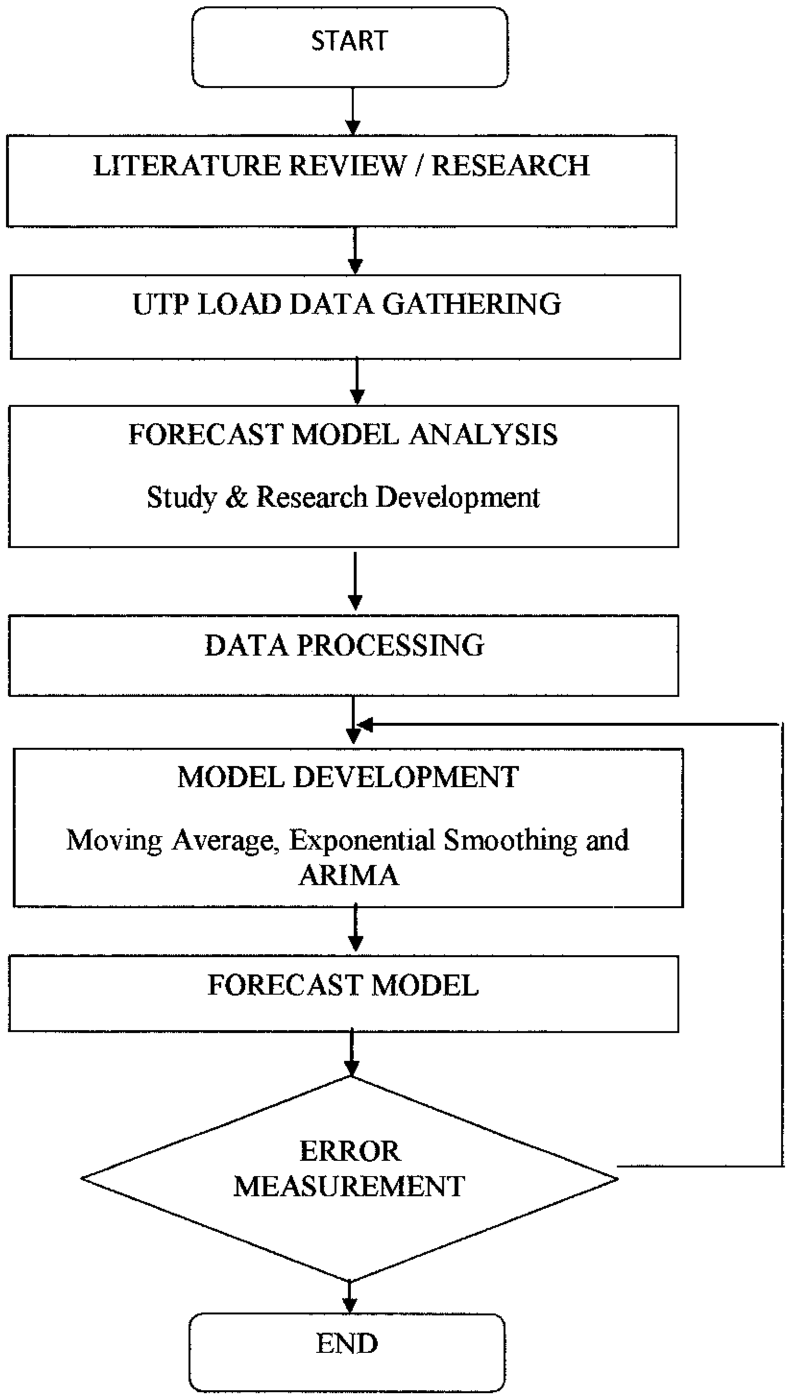



Figure 6: Project's Methodology

### 3.3 Project Duration

In order to effectively monitor the progress of this project, a Gantt chart consists of one year duration had been constructed. See appendix A.

### 3.4 Tool Required

The MATLAB R2010a software is used as the main tool for this forecast method development. MATLAB is an ideal tool for working with moving average and exponential smoothing techniques. The filters Toolbox which is available in MATLAB software also will provide useful tools for working with those techniques along with good commands and organization.

# CHAPTER 4

# RESULTS AND DISCUSSION

## 4.1 Result Using Moving Averages Technique

From the readings obtained, we plot the graph using three types of Moving Average which are Simple Moving Average, Linear Moving Average, and Exponential. The command for moving average is available in MATLAB under Financial Toolbox.

Movavg(Asset, Lead, Lag, Alpha) plots leading and lagging moving averages.

- Asset – Data, a vector of time series readings
- Lead - Number of samples to use in leading average calculation. A positive integer, Lead must be less or equal to Lag
- Lag – Number of samples to use in the lagging average calculation. A positive integer.
- Alpha – (Optional) Control parameter that determines the type of moving averages,.

  0 = simple moving average (default)

  'e' = exponential moving average

### 4.1.1 Semester ON 2010 (Short Term Forecasting)

First of all, the two plots below shows the actual data of the load in UTP during Semester ON of 2010. Note that at first, the plot is free from any smoothing and fitting parameter. Then, we observed the trends of the actual readings and pattern to relate it with the forecasted load later.

As we can see below, we plot the graph using scatter plot as well as line plot to extract more information from actual data such as pattern, trend and cycle.

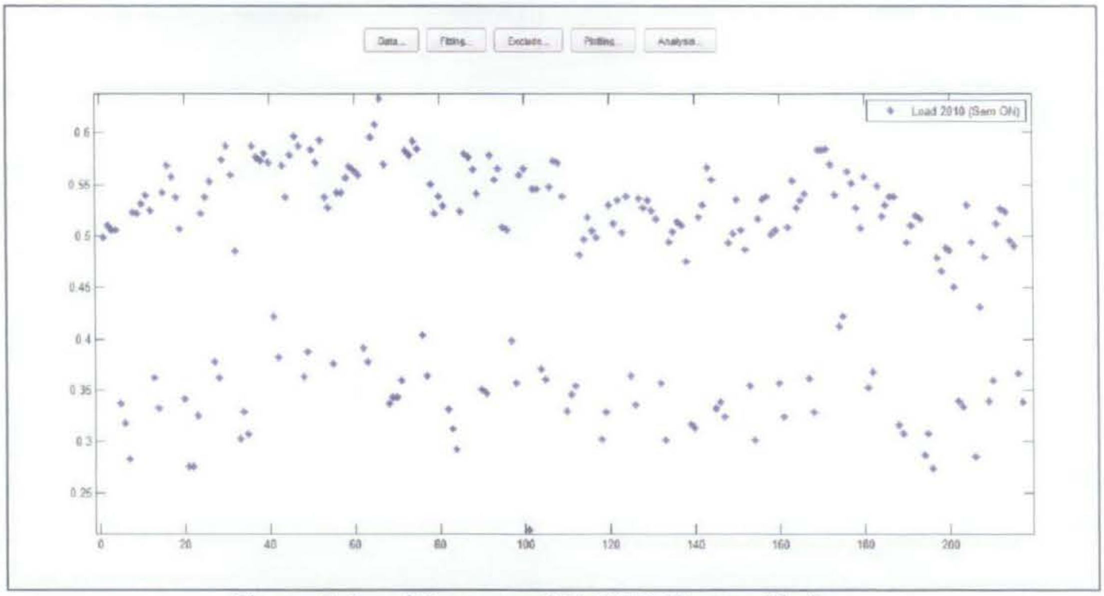



Figure 7: Load Semester ON 2010 (Scatter Plot)

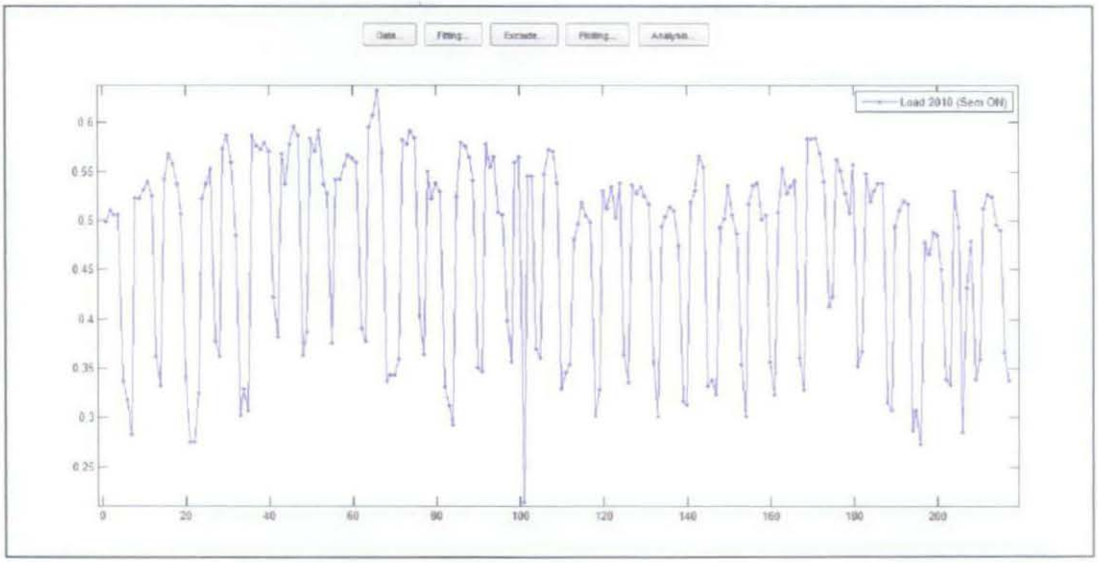



Figure 8: Load Semester ON 2010 (Line Plot)

From the graph, the information can be extracted is as below:

Table 3: Semester ON 2010 Data Info

| Sum (kWh) | Average(kWh) | Max (kWh) | Min(kWh) | Standard Deviation | Variance |
|---|---|---|---|---|---|
| 1021483 | 4707.294931 | 6336 (Day 66) | 2145 (Day 101) | 996.5701799 | 993518.6 |

Note:

Maximum load on Day 66 falls on 13th April 2010. Minimum load on Day 101 falls on 23rd May 2010 during examination week.

Simple Moving Average (Load,3,7,0)

This plots simple 3-sample leading and 7-sample lagging moving average.

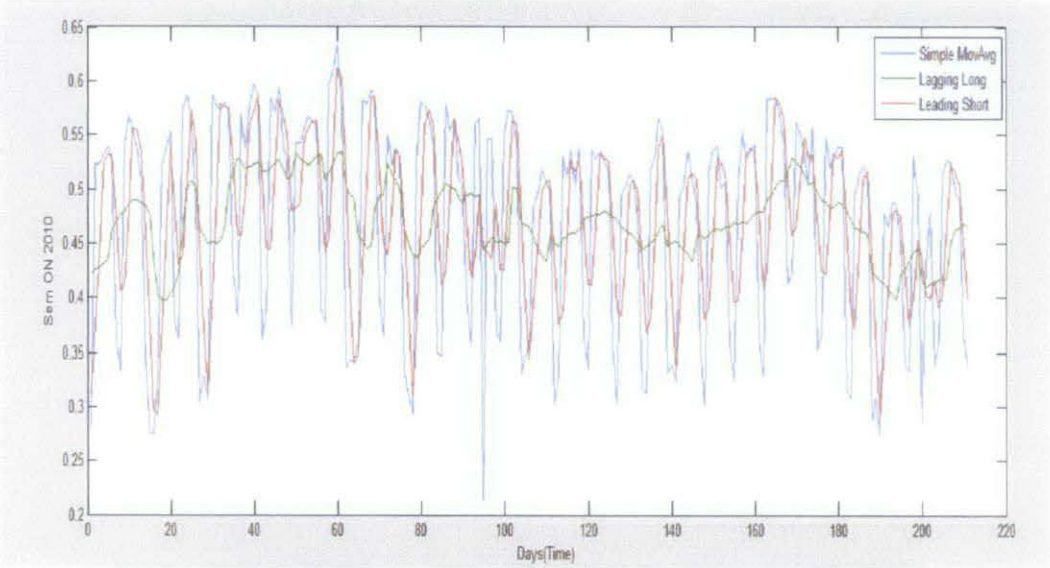



Figure 9: Simple Moving Average (3,7,0) for Semester ON 2010

Simple Moving Average (Load,3,30,0)

This plots simple 3-sample leading and 30-sample lagging moving average.

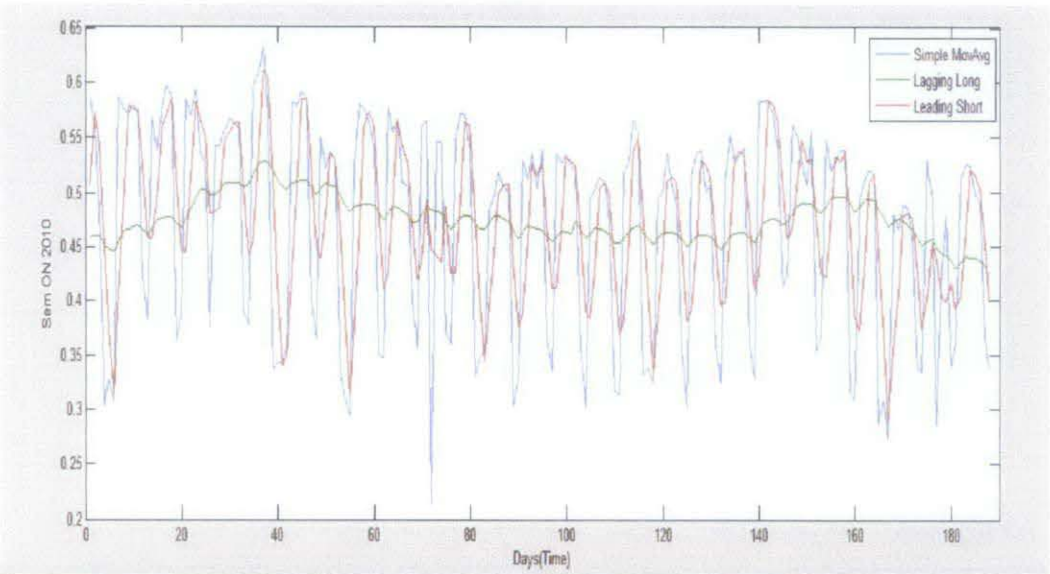



Figure 10: Simple Moving Average (3,30,0) for Semester ON 2010

The reason why we use 3 samples leading is because we want the best identical curve as possible between simple moving average and leading short curve. For the first waveform, we sample it by weekly (using 7 moving average) while for second waveform we sampled it by monthly (using 30 moving average). For early forecast in coming years, we can say that electricity load is quite stable and it will be dropped severely between 70th to 100th days during Semester ON.

Exponential Moving Average (Load,3,7,'e')

This plots exponential 3-sample leading and 7-sample lagging moving average.

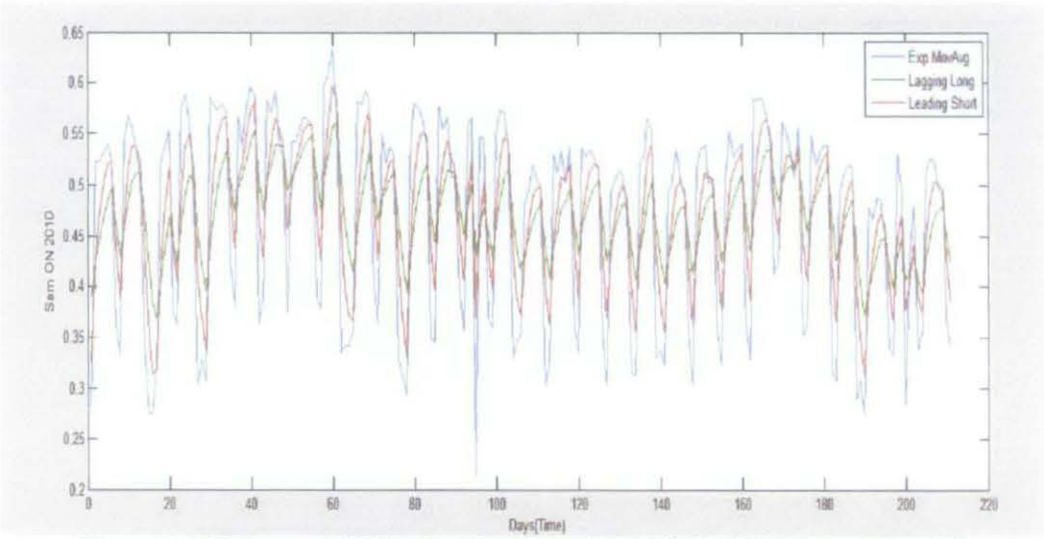



Figure 11: Exponential Moving Average (3,7,'e') for Semester ON 2010

Exponential Moving Average (Load,3,30,'e')

This plots exponential 3-sample leading and 30-sample lagging moving average.

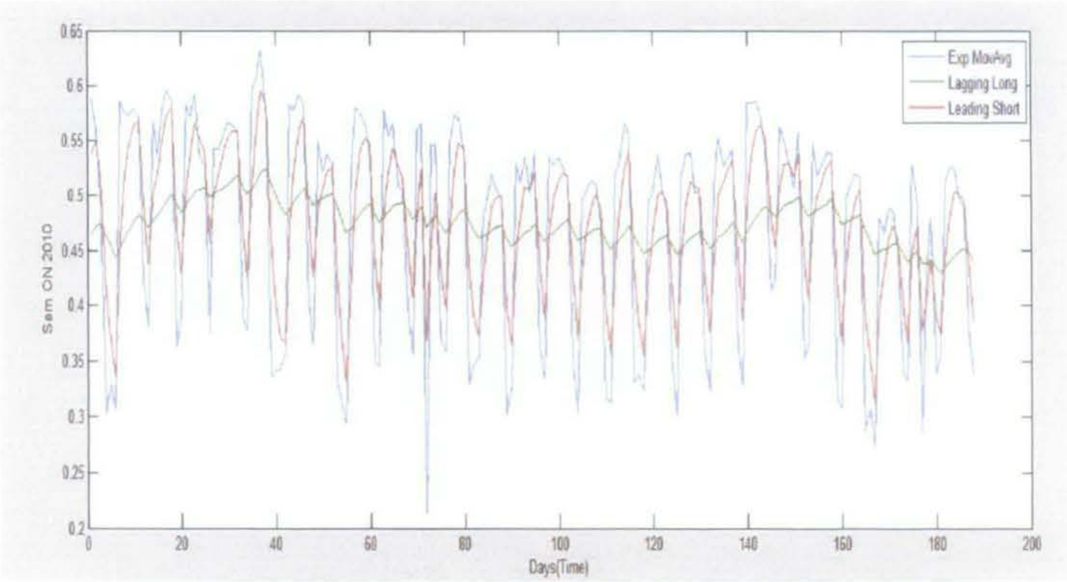



Figure 12: Exponential Moving Average (3,30,'e') for Semester ON 2010

The same reason and forecasting are applied for exponential moving average whereby we used 3 samples leading. However the waveform obtained is quite spiky and responds faster than using simple moving average.

(Note: Please refer Appendix B to see how each semester is divided into days)

### 4.1.2 Semester OFF 2010 (Short Term Forecasting)

First of all, the two plots below shows the actual data of the load in UTP during Semester OFF 2010. The plot is free from any smoothing and fitting parameter. We observe the trends of the actual readings and pattern to relate it with the forecasted load later.

As we can see below, we plot the graph using scatter plot as well as line plot to provide us with more information from actual data.

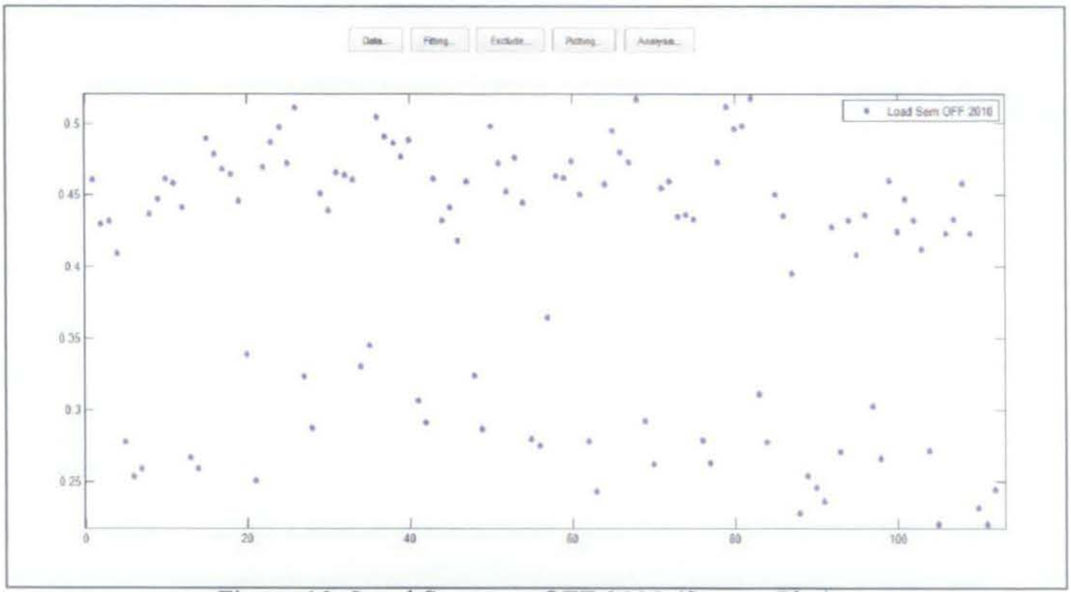


Figure 13: Load Semester OFF 2010 (Scatter Plot)

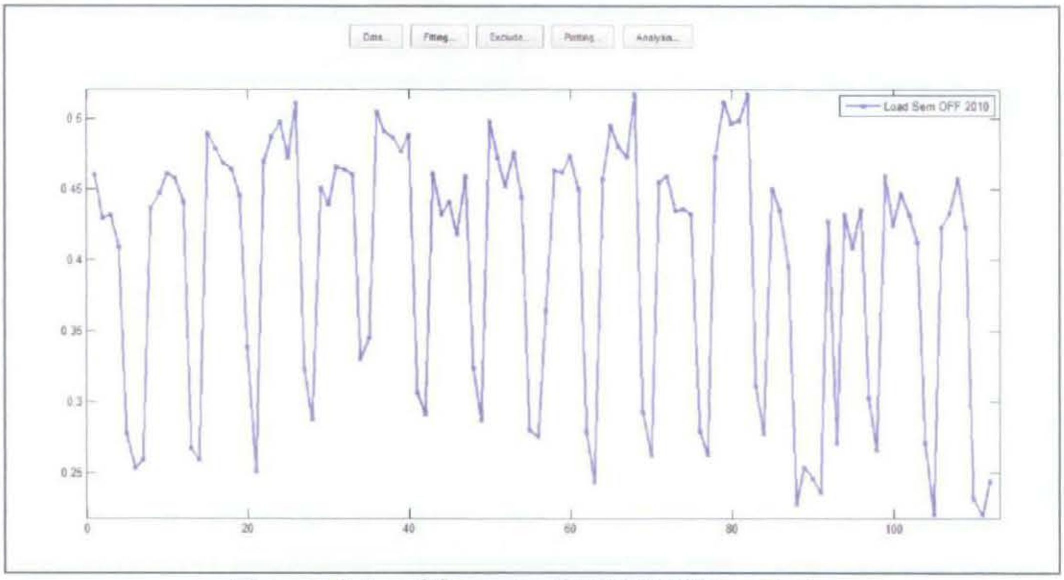


Figure 14: Load Semester OFF 2010 (Line Plot)

From the graph, the information can be extracted as below:

Table 4: Semester OFF 2010 Data Info

| Sum (kW) | Average(kW) | Max (kW) | Min (kW) | Standard Deviation | Variance |
|---|---|---|---|---|---|
| 444860 | 3971 | 5180 (Day 82) | 2204 (Day 104) | 918 | 839158 |

Note:

Maximum load on 82nd day falls on 18th December 2010. Minimum load on 104th day falls on 9th January 2011.

Simple Moving Average (Load,3,7,0)

This plots simple 3-sample leading and 7-sample lagging moving average.

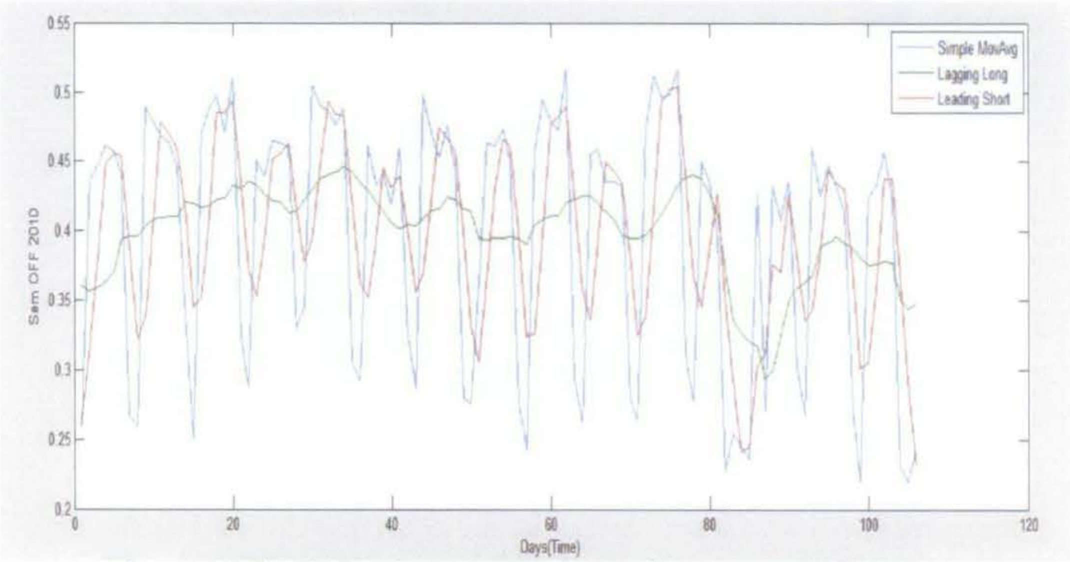



Figure 15: Simple Moving Average (3,7,0) for Semester OFF 2010

Simple Moving Average (Load,3,30,0)

This plots simple 3-sample leading and 30-sample lagging moving average.

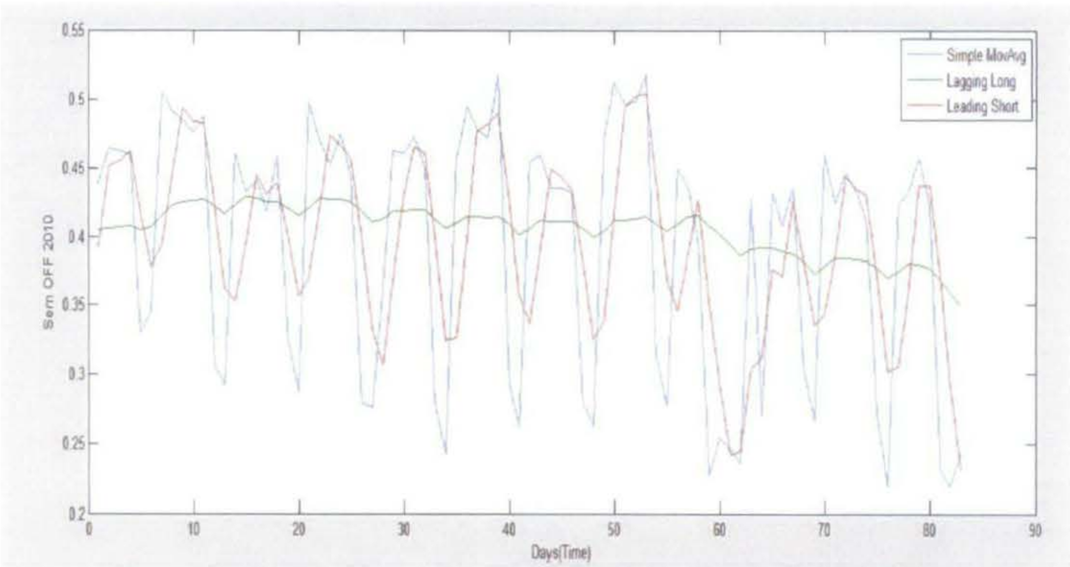



Figure 16: Simple Moving Average (3,30,0) for Semester OFF 2010

For the first graph, we sample it by weekly (using 7 moving average) while for second graph we sampled it by monthly (using 30 moving average). For early forecast, we can say that electricity load is quite stable when we sampled it by weekly while for monthly sampled it is unstable. Hence, forecasting for Semester OFF using weekly basis is much better.

The graphs show more smooth pattern compared to the one that used exponential smoothing average. It can be said that simple moving average is suitable to identify short-term fluctuations.

<u>Exponential Moving Average (Load,3,7,'e')</u>

This plots exponential 3-sample leading and 7-sample lagging moving average.

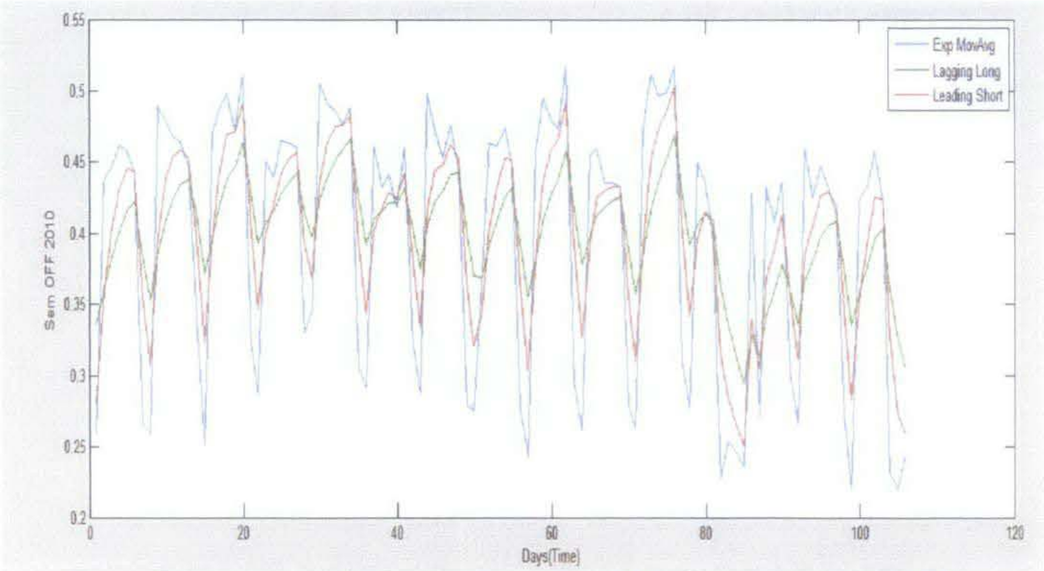



Figure 17: Exponential Moving Average (3,7,'e') for Semester OFF 2010

Exponential Moving Average (Load,3,30,'e')

This plots exponential 3-sample leading and 30-sample lagging moving average.

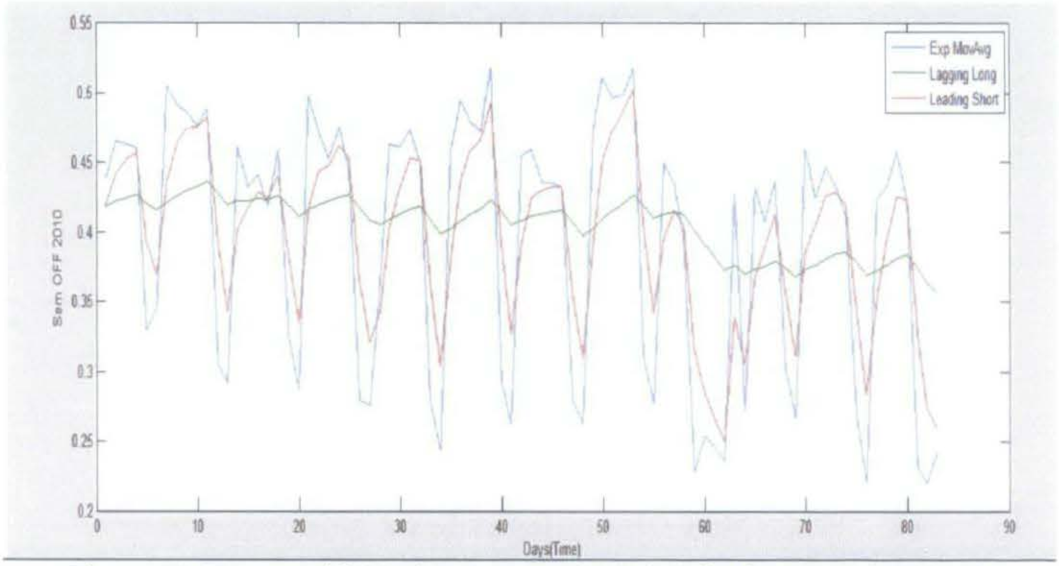



Figure 18: Exponential Moving Average (3,30,'e') for Semester OFF 2010

For the first graph, we sample it by weekly (using 7 moving average) while for second graph we sampled it by monthly (using 30 moving average). We can say the same thing for exponential moving average which is weekly basis sampled is much better to predict the electricity load. The lowest electricity load is about 60th-80th days during Semester OFF.

(Note: Please refer Appendix B to see how each semester is divided into days)

### 4.1.3 Semester ON 2006-2010 (Long Term Forecasting)

First of all, the two plots below shows the actual data of the load in UTP during Semester ON of 2006 to 2010. Note that the plot is free from any smoothing and fitting parameter. Then, we observed the trends of the actual readings and pattern to relate it with the forecasted load later.

As we can see below, we plot the graph using scatter plot as well as line plot to extract more information from actual data.

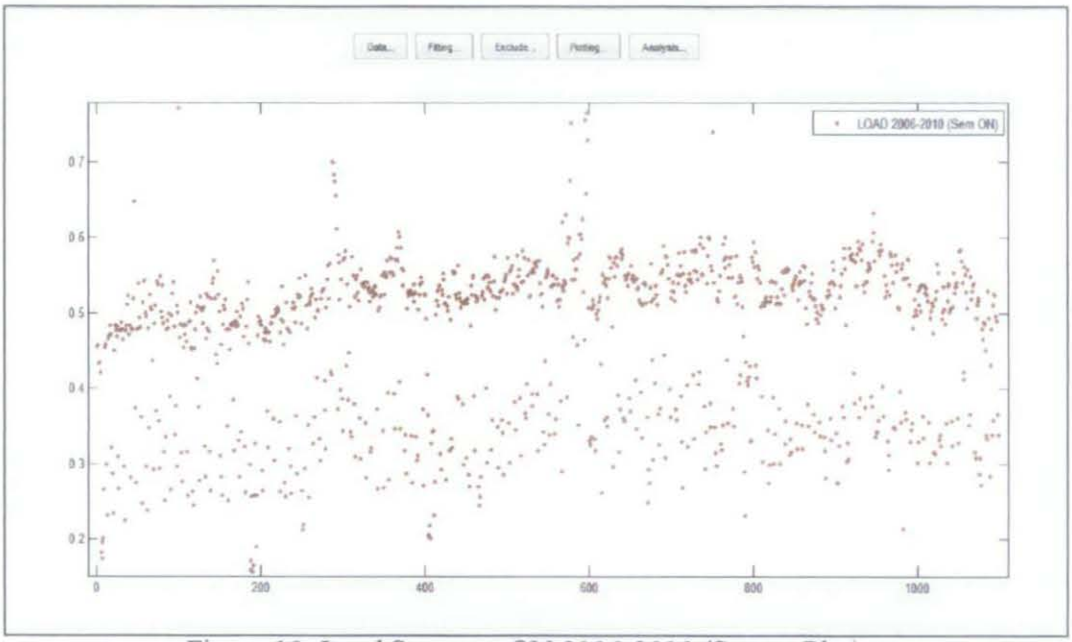



Figure 19: Load Semester ON 2006-2010 (Scatter Plot)

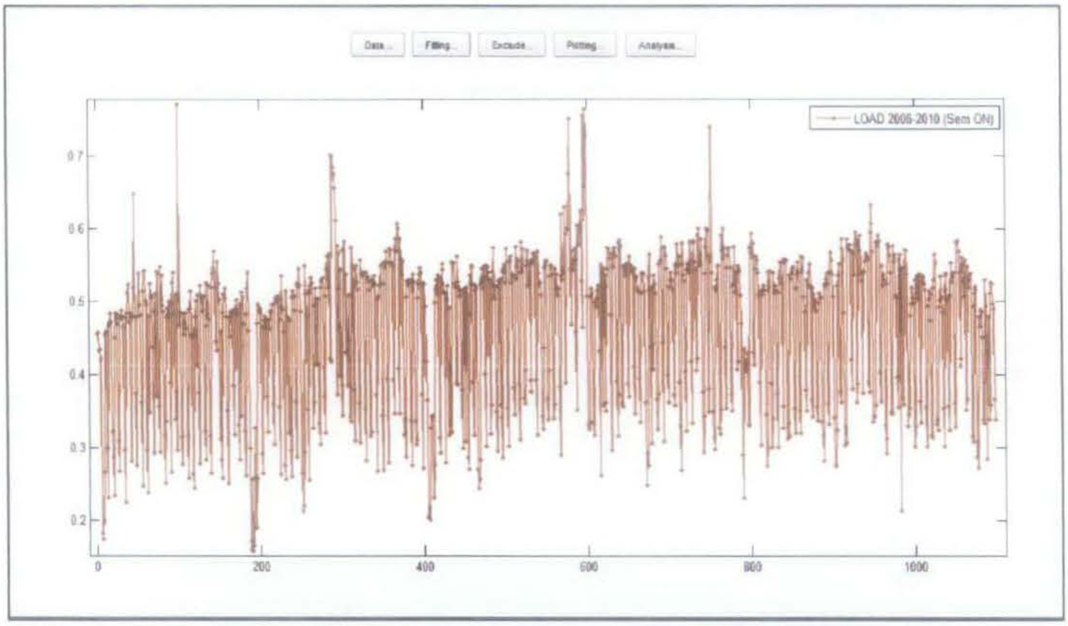



Figure 20: Load Semester ON 2006-2010 (Line Plot)

From the plots above, we can observe that there are more points ranging from 0.4 to 0.6 than any other parts of the graph. The highest point is about 0.75 while the lowest point plotted is about 0.1.

From the graph, the information can be extracted as below:

Table 5: Semester ON 2006-2010 Data Info

| Sum (kW) | Average (kW) | Max (kW) | Min (kW) | Standard Deviation | Variance |
|---|---|---|---|---|---|
| 5099793 | 4640 | 7728 (Day 101) | 1580 (Day 191) | 1070 | 1145402 |

Note:

Maximum load on 101st day falls on 20th May 2006 which is during examination week. Minimum load on 191st day falls on 19th October 2006.

Simple Moving Average (Load,3,7,0)

This plots simple 3-sample leading and 7-sample lagging moving average.

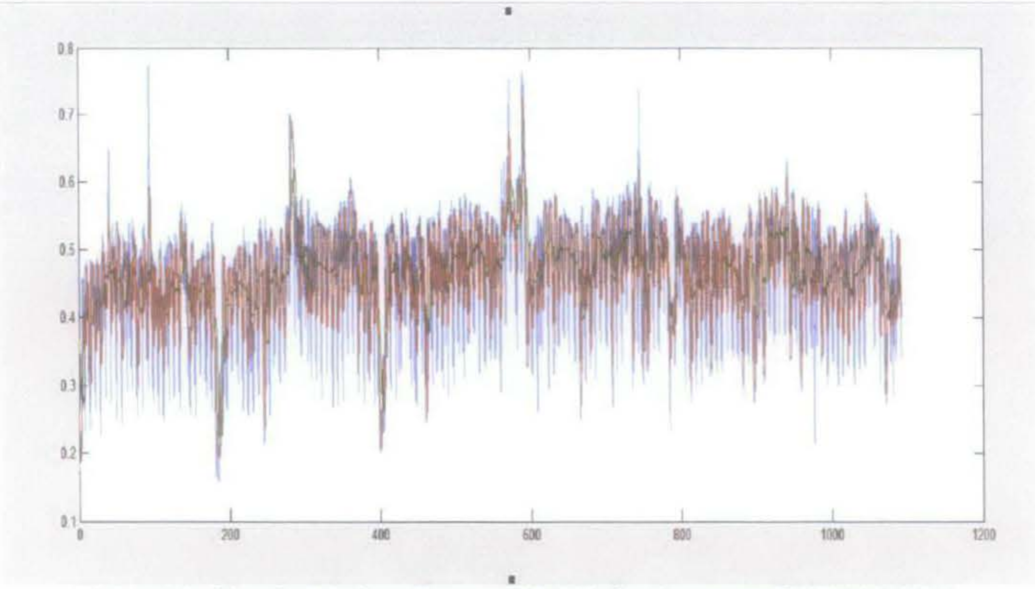



Figure 21: Simple Moving Average (3,7,0) for Semester ON 2006-2010

Simple Moving Average (Load,3,30,0)

This plots simple 3-sample leading and 7-sample lagging moving average.

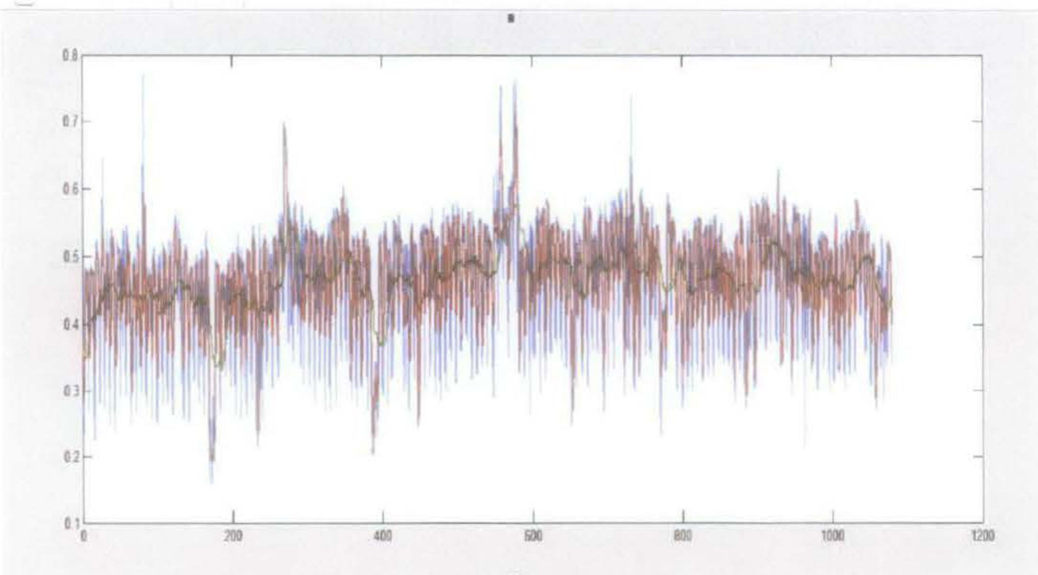



Figure 22: Simple Moving Average (3,30,0) for Semester ON 2006-2010

Since we are running many data, the graphs are also compressed. But somehow we still manage to observe the fluctuations in the graphs due to high difference between previous and next moving averages plotted. For early forecast, there will be high electricity load which is about 7500 kWh on 550th to 600th day during Semester ON. The lowest electricity consumption will be on 190th to 200th day during Semester ON.

Exponential Moving Average (Load,3,7,'e')

This plots exponential three-sample leading and 7-sample lagging moving average.

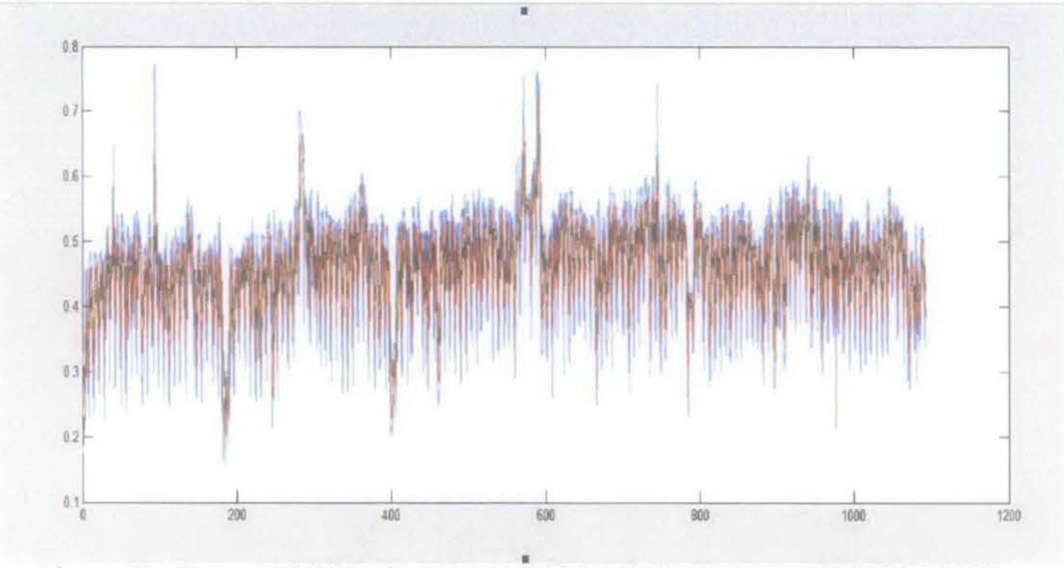



Figure 23: Exponential Moving Average (3,7,'e') for Semester ON 2006-2010

Exponential Moving Average (Load,3,30,'e')

This plots exponential 3-sample leading and 30-sample lagging moving average.

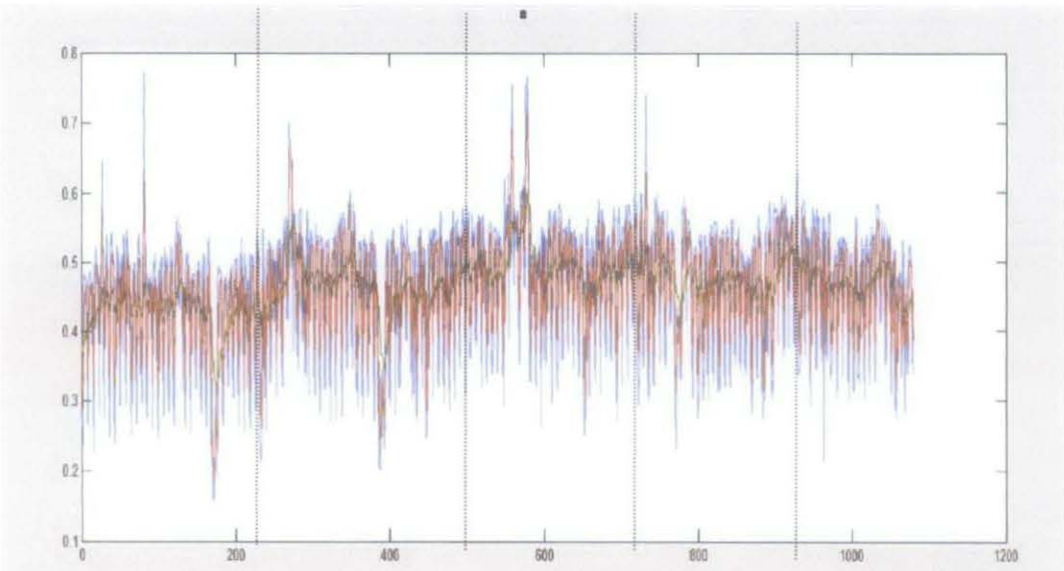



Figure 24: Exponential Moving Average (3,30,'e') for Semester ON 2006-2010

The same observation can be applied in the exponential moving average case whereby many data has been used. However, the interpolation seems to be less smooth and more rapid signal. In this case, the monthly basis prediction is more preferable rather than weekly due to matching appearance and harmony of the graph. The graph also can be divided into five section as illustrated above which can be used to forecast load in next five years.

(Note: Please refer Appendix B to see how each semester is divided into days)

### 4.1.4 Semester OFF 2006-2010 (Long Term Forecasting)

First of all, the two plots below shows the actual data of the load in UTP during Semester OFF of 2006 to 2010. The plot is free from any smoothing and fitting parameter. We observed the trends of the actual readings and pattern to relate it with the forecasted load later. As we can see below, we plot the graph using scatter plot as well as line plot to provide us with more information from actual data.

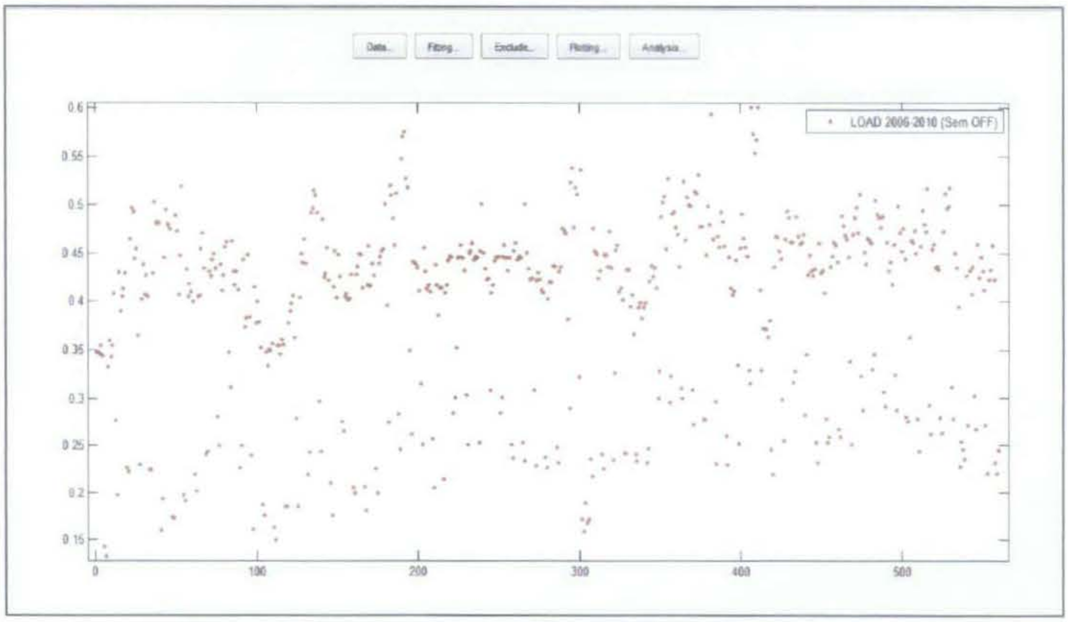


Figure 25: Load Semester OFF 2006-2010 (Scatter Plot)

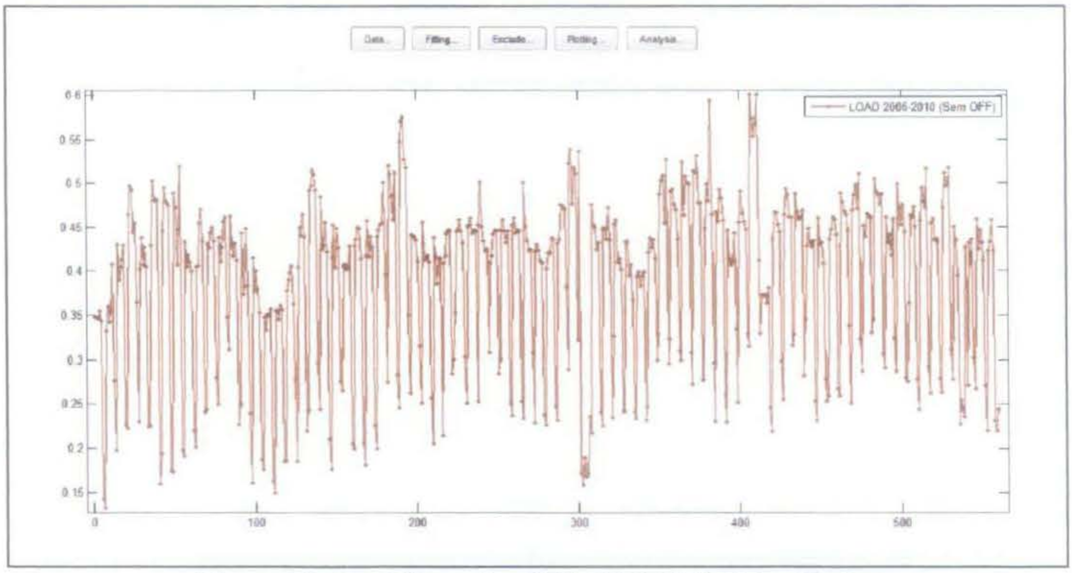



Figure 26: Load Semester OFF 2006-2010 (Line Plot)

From the graph, the information can be extracted as table below:

Table 6: Semester OFF 2006-2010 Data Info

| Sum (kW) | Average (kW) | Max (kW) | Min (kW) | Standard Deviation | Variance |
|---|---|---|---|---|---|
| 2179289 | 3892 | 6010 (Day 407) | 1332 (Day 7) | 987 | 973883 |

Note:

Maximum load on $407^{st}$ day falls on $3^{rd}$ December 2009. Minimum load on $7^{th}$ day falls on $18^{th}$ March 2006.

Simple Moving Average (Load,2,7,0)

This plots simple 2-sample leading and 7-sample lagging moving average.

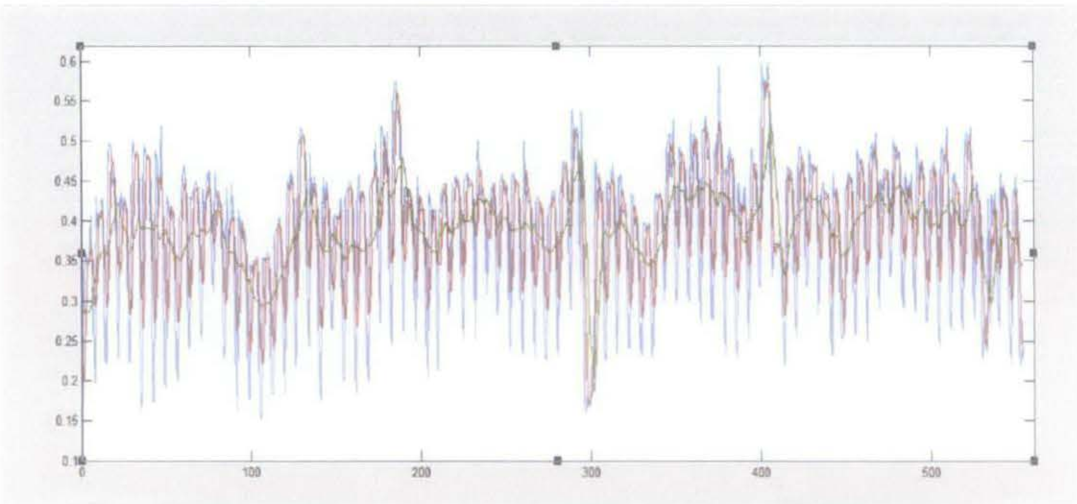



Figure 27: Simple Moving Average (2,7,0) for Semester OFF 2006-2010

Simple Moving Average (Load,2,30,0)

This plots simple 2-sample leading and 30-sample lagging moving average.

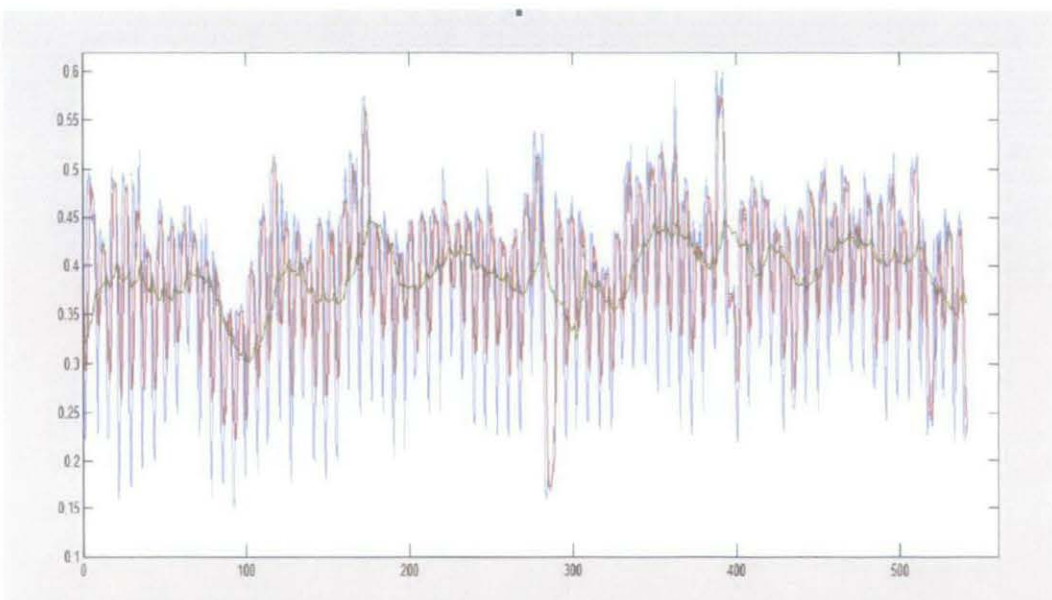



Figure 28: Simple Moving Average (2,30,0) for Semester OFF 2006-2010

For this case, we used 2 samples leading. The reason why we use 2 samples leading is because we want the best similar waveform as possible between simple moving average and leading short curve. For the first graph, we sample it by weekly (using 7 moving average) while for second graph we sampled it by monthly (using

30 moving average). The weekly basis forecast is more preferable compare to monthly basis. For early forecast in coming years, we can predict that highest electricity load is on day 70 during Semester OFF and the rest is just normal consumption of electricity load.

Exponential Moving Average (Load,2,7,'e')

This plots exponential 2-sample leading and 7-sample lagging moving average.

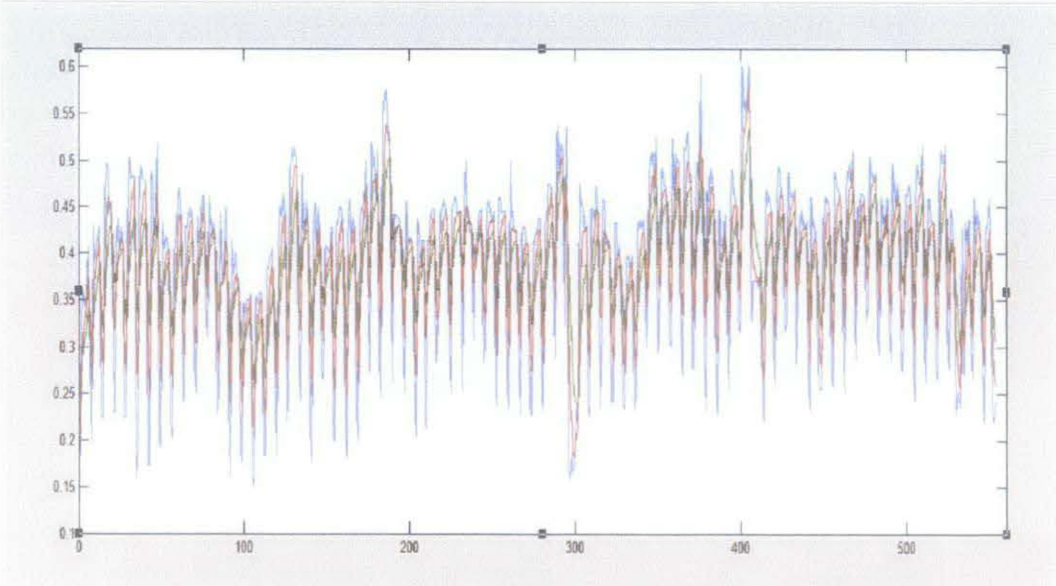



Figure 29: Exponential Moving Average (2,7'e') for Semester OFF 2006-2010

Exponential Moving Average (Load,2,30,'e')

This plots exponential 2-sample leading and 30-sample lagging moving average.

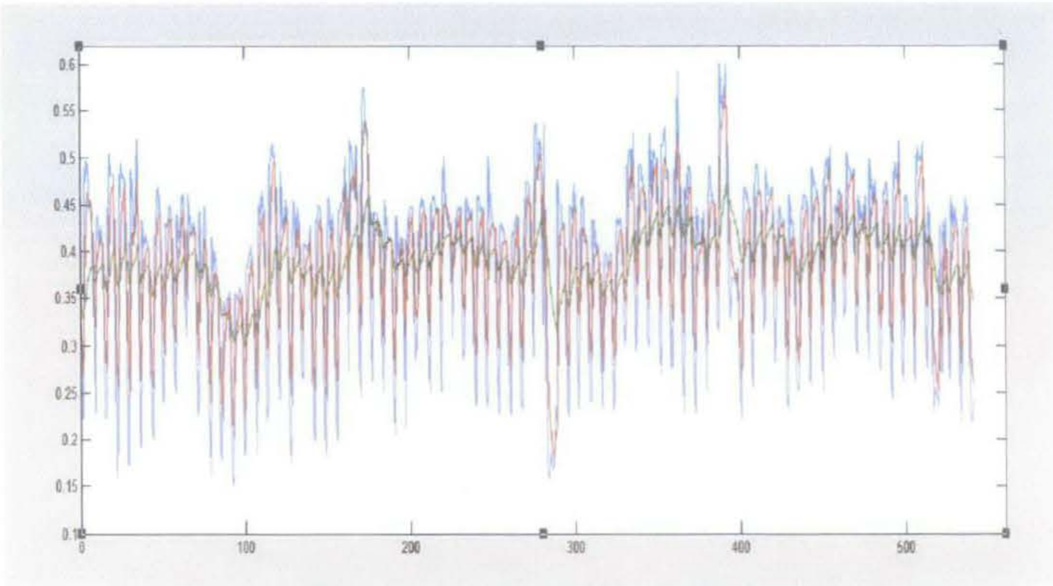


Figure 30: Exponential Moving Average (2,30'e') for Semester OFF 2006-2010

The same forecast can be used for exponential moving average except that the trending is much faster with higher responsiveness. The monthly basis sampled is the best prediction for this case.

(Note: Please refer Appendix B to see how each semester is divided into days)

## 4.2 Result Using Exponential Smoothing Technique

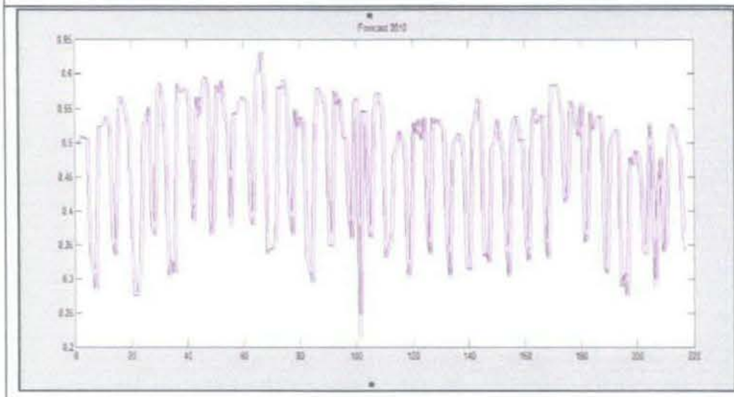
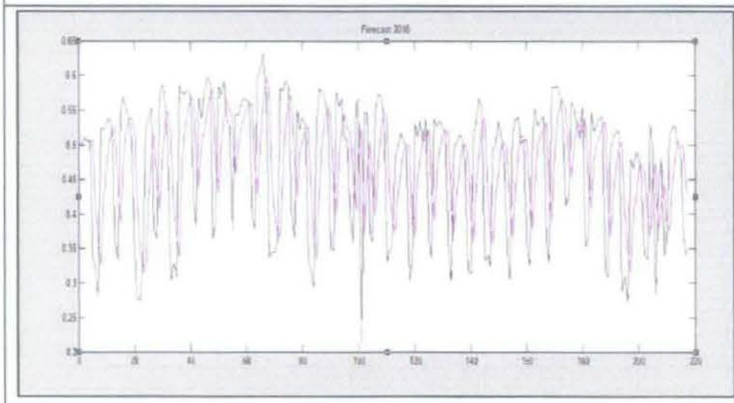
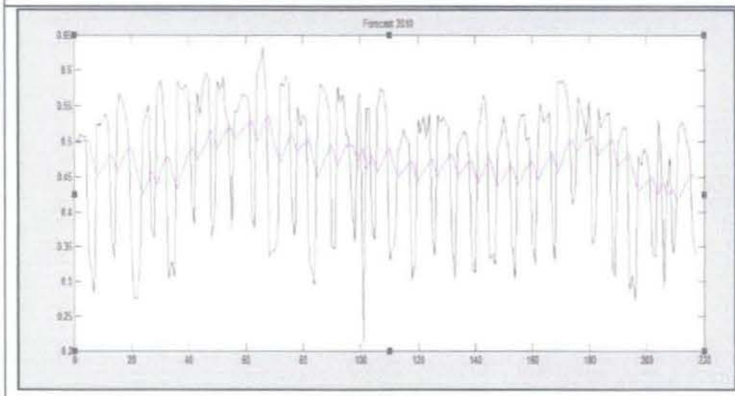
**Short-Term Load Forecasting**

For short term load forecasting in UTP, we used year duration of data of 2010. The data then divided into two parts which are taken during Semester ON and Semester OFF. After that, we forecast the load in UTP for the next year namely 2011 by using exponential smoothing technique in MATLAB.

### 4.2.1 Semester ON 2010

After that, we use MATLAB simulation to simulate another plot using exponential smoothing technique. Then, we compare the behaviour of the graph plotted when we vary the alpha ($\alpha$) from 0 to 0.9 of the exponential smoothing equation. Note that the raw data is plotted in black, while smoothed data is plotted in magenta.

Table 7: Forecast Load Semester ON 2010 with various $\alpha$.

| Graph Plot | Discussion |
|---|---|
|  $\alpha = 0$ | The plot of smoothed data is almost follows the plotted raw data. In this case, this is not the best forecast model because of the similarity between actual value and forecasted value. |
|  $\alpha = 0.5$ | For this value of alpha, the plot of smoothed data obtained is smaller than actual plot. It will not be able to fulfil the next years load demand thus not recommended. |
|  $\alpha = 0.9$ | In this case, the graph plotted is absolutely lesser than the actual graph. The magenta line is more linear than the black line. Thus, we will not consider this plot. |

As we can see, as we increase the value of alpha from 0 to 1, there will be much impact to the graph plotted. It also means more emphasis would be given on the previous estimated data than on the actual data.

When $\alpha$ close to 1 will have an adjustment value that is substantial, making the forecast more sensitive to swings in past historical demand based on the previous period's error. The closer $\alpha$ value to 1, the more reactive the future forecast will be.

When $\alpha$ value is close to 0, the forecast will include very little adjustment, making it less sensitive to past swings in demand. In this case, future demand forecasts will be much smoothed, not reflecting any prior swings in demand.

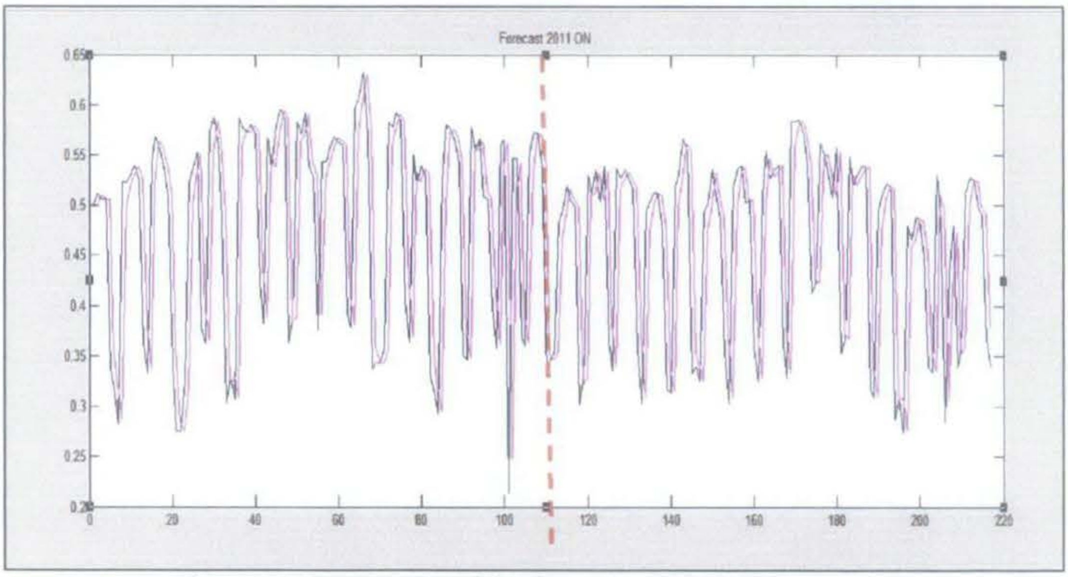



Figure 31: Forecast Load for Semester ON 2010 ($\alpha = 0.3$)

The graph above best load forecast value with minimal error. It is plotted when the value of alpha is 0.3. The plotted graph is smoothed with very little adjustment and it is more emphasis is on the actual data than on estimation capability.

We can analyze that the pattern of the graph which is almost the same when it is divided into two sections. It explains the load forecasted for 2011 will be in approximately these patterns. The highest load is measured falls on about $70^{th}$ day which is about $0.63 \times 10^6$ MWatt while the lowest load is measured falls on about $102^{th}$ day which is about $0.25 \times 10^6$ MWatt.

For our forecasting, we have calculated and measured an error which is Mean Absolute Percentage Error (MAPE).

. Mean absolute percentage error (MAPE) near 0 (zero) can be produced by large positive and negative percentage errors that cancel each other out. Thus, a better measure of relative overall fit is the mean absolute percentage error. Also, this measure is usually more meaningful than the mean squared error.

As we increase the alpha value from 0 to 1 by increment of 0.1, we can see that the errors are also increase. This suggesting that the closer the alpha value to 0 will pick up more of the peaks and valleys associated with the historical demand, thus reducing the error. However, the least error will not indicate that it is the best forecasting model as we need to consider other criteria as well.

The summary of errors calculated is shown in the table below.

Table 8: List of Forecast Error Semester ON 2010 with various α.

| **Alpha (α)** | **Mean Absolute Percentage Error (MAPE) (%)** |
|---|---|
| 0 | 0 |
| 0.1 | 3.3998 |
| 0.2 | 6.8728 |
| **0.3** | **12.9994** |
| 0.4 | 14.0540 |
| 0.5 | 17.5482 |
| 0.6 | 20.5752 |
| 0.7 | 22.5821 |
| 0.8 | 22.868 |
| 0.9 | 21.4652 |
| 1.0 | 35.8388 |

Below is the manual calculation of average value of forecast load when we are using $\alpha$ between range of 0.25 to 0.35 to prove that $\alpha = 0.3$ is the best.

Table 9: Calculation of forecast load ($0.25 < \alpha < 0.35$)

| Day | Load (MWatt ) | Forecast Load (MWatt) |
|---|---|---|
| 1 | 4988 | 4327 |
| 2 | 5112 | 4988 |
| 3 | 5064 | 5100 |
| 4 | 5060 | 5068 |
| 5 | 3372 | 5061 |
| 6 | 3184 | 3541 |
| 7 | 2828 | 3220 |

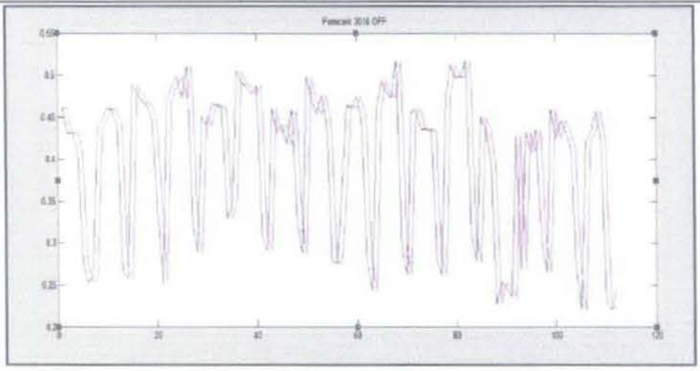
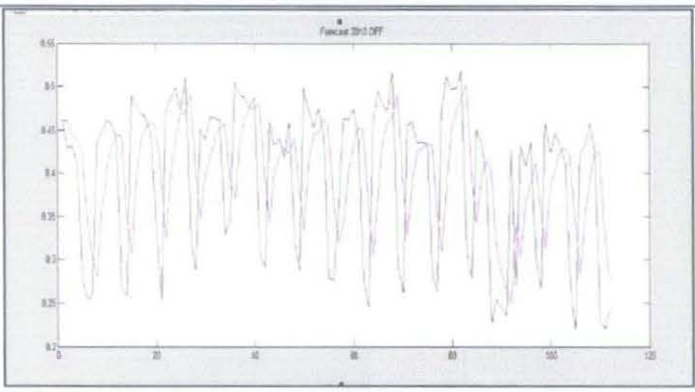
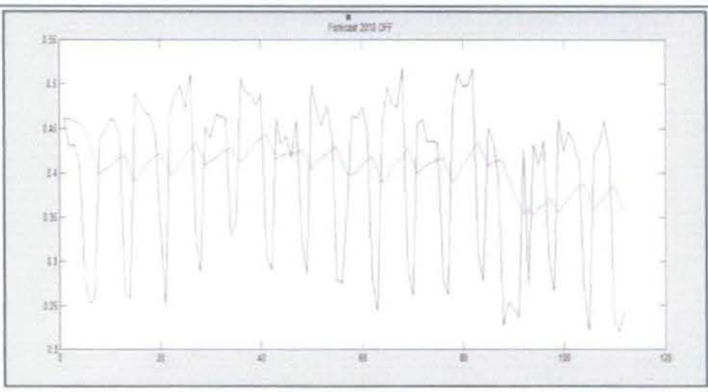
Therefore it can be concluded that to forecast the load for Semester ON 2011, the alpha value should be equal to 0.3. In this case we are using exponential smoothing technique based on Semester ON 2010 raw data.

### 4.2.2 Semester OFF 2010

After that, we use MATLAB simulation to simulate another plot using exponential smoothing technique. Then, we compare the behaviour of the graph plotted when we vary the alpha ($\alpha$) from 0 to 0.9 of the exponential smoothing equation. Note that the raw data is plotted in black, while smoothed data is plotted in magenta.

For this part, we compare the behaviour of the graph plotted when we vary the alpha ($\alpha$) from 0 to 0.9. Notice that the raw data is plotted in black, while smoothed data is plotted in magenta.

Table 10: Forecast Load Semester OFF 2010 with various $\alpha$.

| Graph Plot | Discussion |
|---|---|
|  $\alpha = 0$ | The plot of smoothed data is like the shadow of the plot of raw actual data. In this case, alpha equal to 0 is not the best forecast model because of the exactness between actual value and forecasted value. |
|  $\alpha = 0.5$ | For this value of alpha, the plot of smoothed data obtained is lesser than actual plot. It will not be able to fulfil the 2011 load demand thus not recommended. |
|  $\alpha = 0.9$ | In this case, the graph plotted is absolutely lesser than the actual graph. Thus, the plot will not be considered. |

As we can see, as we increase the value of alpha from 0 to 1, there will be much impact to the graph plotted. It also means more emphasis would be given on the previous estimated data than on the actual data. From the table above, when applied recursively to each successive observation in the series, each new smoothed value (forecast) is computed as the weighted average of the current observation and the previous smoothed observation. Thus, in effect, each smoothed value is the weighted average of the previous observations, where the weights decrease exponentially depending on the value of parameter α.

If α is equal to 1 (one) then the previous observations are ignored entirely; if α is equal to 0 then the current observation is ignored entirely, and the smoothed value consists entirely of the previous smoothed value (which in turn is computed from the smoothed observation before it, and so on thus all smoothed values will be equal to the initial smoothed value). Values of α in-between will produce intermediate results.

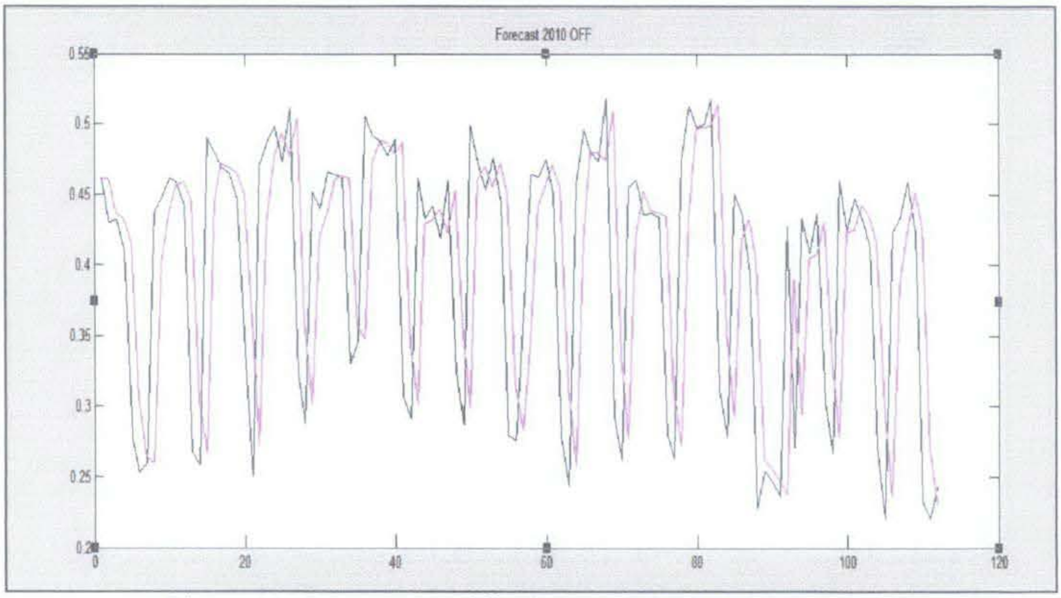



Figure 32: Forecast Load for Semester OFF 2010 ($\alpha = 0.3$)

It is plotted when the value of alpha is 0.3. The plotted graph is smoothed with very little adjustment and it is more emphasis is on the actual data than on estimation capability. The highest load is measured falls on about 84th day which is about $0.53 \times 10^6$ MWatt while the lowest load is measured falls on about 105th and 109th day which is about $0.23 \times 10^6$ MWatt.

For our forecasting, we have calculated and measured an error which is Mean Absolute Percentage Error (MAPE). As we increase the alpha value from 0 to 1 by increment of 0.1, we can see that the errors are also increase. This suggesting that the closer the alpha value to 0 will pick up more of the peaks and valleys associated with the historical demand, thus reducing the error. However, the least error will not indicate that it is the best forecasting model as we need to consider other criteria as well.

The summary of errors calculated is shown in the table below.

Table 11: Forecast Error Semester OFF 2010 with various α.

| **Alpha (α)** | **Mean Absolute Percentage Error (MAPE) (%)** |
|---|---|
| 0 | 0 |
| 0.1 | 1.1402 |
| 0.2 | 7.6311 |
| **0.3** | **14.4330** |
| 0.4 | 16.3926 |
| 0.5 | 24.4939 |
| 0.6 | 33.5172 |
| 0.7 | 42.9938 |
| 0.8 | 52.4392 |
| 0.9 | 61.3656 |
| 1.0 | 70.2559 |

Below is the manual calculation of average value of forecast load when we are using α between range of 0.25 to 0.35 to prove that α = 0.3 is the best.

Table 12: Calculation of forecast load ($0.25 < \alpha < 0.35$)

| Day | Load (MWatt) | Forecast Load (MWatt) |
|---|---|---|
| 1 | 4612 | 4637 |
| 2 | 4304 | 4612 |
| 3 | 4325 | 4366 |
| 4 | 4096 | 4332 |
| 5 | 2780 | 4143 |
| 6 | 2536 | 3053 |
| 7 | 2596 | 2639 |

Therefore it can be concluded that to forecast the load for Semester OFF 2011, the alpha value should be equal to 0.3. In this case we are using exponential smoothing technique based on Semester OFF 2010 raw data.

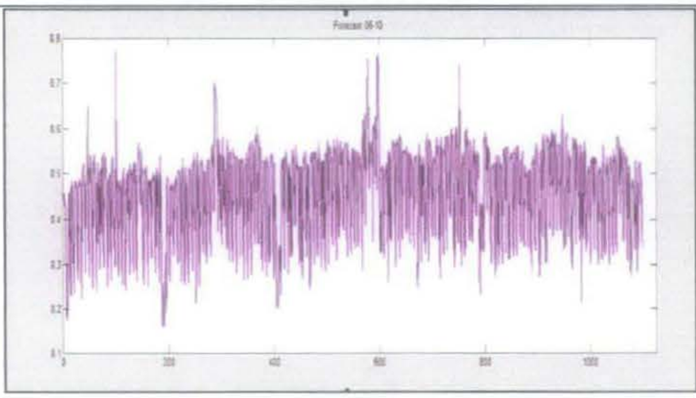
**Long-Term Load Forecasting**

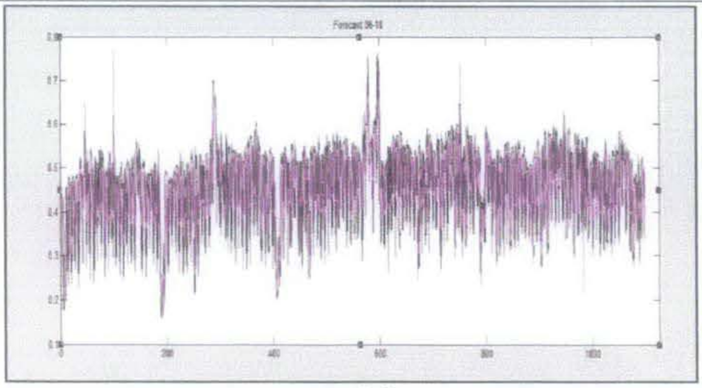
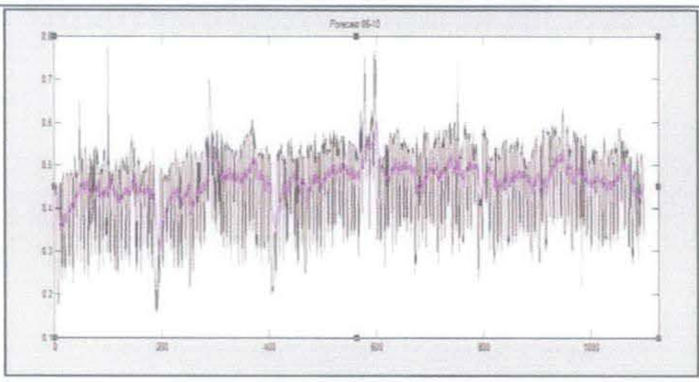
For long term load forecasting in UTP, we used 5 years duration of data ranging from 2006 to 2010. The data then divided into two parts which are taken during Semester ON and Semester OFF. After that, we forecast the load in UTP for the next 5 years namely 2011 to 2015 by using exponential smoothing technique in MATLAB.

### 4.2.3 Semester ON 2006-2010

After that, we use MATLAB simulation to simulate another plot using exponential smoothing technique. Then, we compare the behaviour of the graph plotted when we vary the alpha ($\alpha$) from 0 to 0.9 of the exponential smoothing equation. Note that the raw data is plotted in black, while smoothed data is plotted in magenta.

Table 13: Forecast Load Semester ON 2006-2010 with various $\alpha$.

| Graph Plot | Discussion |
|---|---|
|  $\alpha = 0$ | The plot of smoothed data is almost the same as the plot of raw actual data. In this case, alpha equal to 0 is not the best forecast model because of the exactness between actual value and forecasted value. |

| | |
|---|---|
|  $\alpha = 0.5$ | For this value of alpha, the plot of smoothed data obtained is lesser than actual plot. It will not be able to fulfil the next 5 years load demand thus not recommended. |
|  $\alpha = 0.9$ | In this case, the smoothed data plotted is absolutely smaller than the actual plot. The magenta line is more linear than the black line. Thus, we will not consider this plot. |

From the table above, when $\alpha$ close to 1 will have an adjustment value that is substantial, making the forecast more sensitive to swings in past historical demand based on the previous period's error. The closer $\alpha$ value to 1, the more reactive the future forecast will be.

When $\alpha$ value is close to 0, the forecast will include very little adjustment, making it less sensitive to past swings in demand. In this case, future demand forecasts will be much smoothed, not reflecting any prior swings in demand.

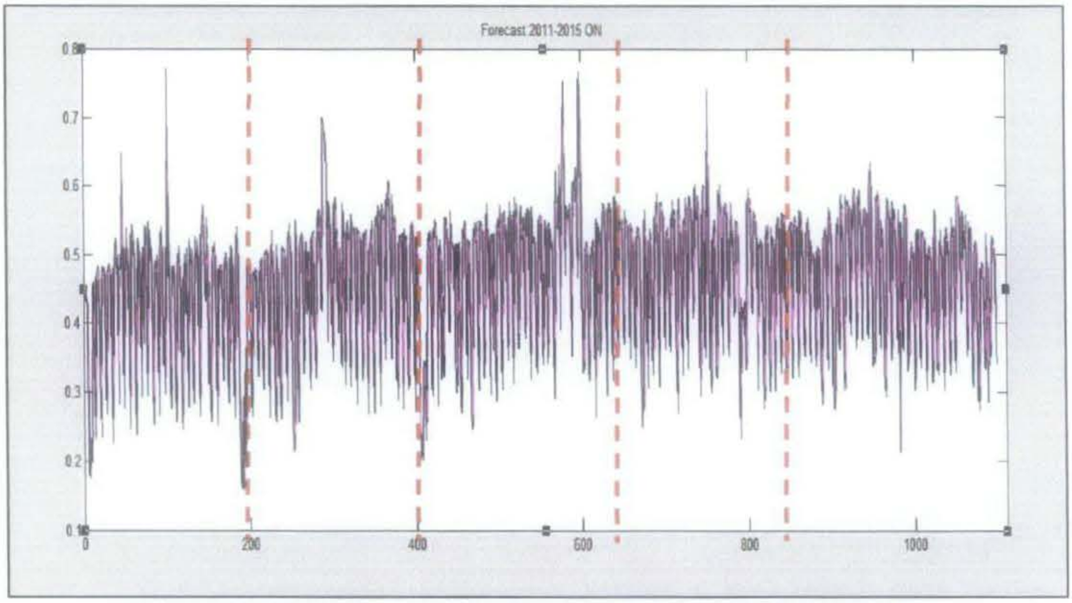


Figure 33: Forecast Load for Semester ON 2006-2010 ($\alpha = 0.3$)

The graph above shows best load forecast value with minimal error. It is plotted when the value of alpha is 0.3. The plotted graph is smoothed with very little adjustment and it is more emphasis is on the actual data than on estimation capability.

There are five identical cycles from the graph above. We can analyze that the pattern of the graph which is almost the same when it is divided into five sections. It explains the load forecasted for the next five years will be in these patterns. The highest load is measured falls on about 600$^{th}$ day which is about $0.78 \times 10^6$ MWatt while the lowest load is measured falls on about 195$^{th}$ day which is about $0.15 \times 10^6$ MWatt.

For our forecasting, we have calculated and measured Mean Absolute Percentage Error (MAPE). As we increase the alpha value from 0 to 1 by increment of 0.1, we can see that the errors are also increase. This suggesting that the closer the alpha value to 0 will pick up more of the peaks and valleys associated with the historical demand, thus reducing the error. However, the least error will not indicate that it is the best forecasting model as we need to consider other criteria as well.

The summary of errors calculated is shown in the table below.

Table 14: Forecast Error Semester ON 2006-2010 with various α.

| Alpha (α) | Mean Absolute Percentage Error (MAPE) (%) |
|---|---|
| 0 | 0 |
| 0.1 | 4.3998 |
| 0.2 | 7.8728 |
| **0.3** | **14.4301** |
| 0.4 | 16.0540 |
| 0.5 | 18.5482 |
| 0.6 | 20.5752 |
| 0.7 | 22.5821 |
| 0.8 | 22.8680 |
| 0.9 | 21.4625 |
| 1.0 | 24.2919 |

Below is the manual calculation of average value of forecast load when we are using α between range of 0.25 to 0.35 to prove that α = 0.3 is the best.

Table 15: Calculation of forecast load (0.25 < α < 0.35)

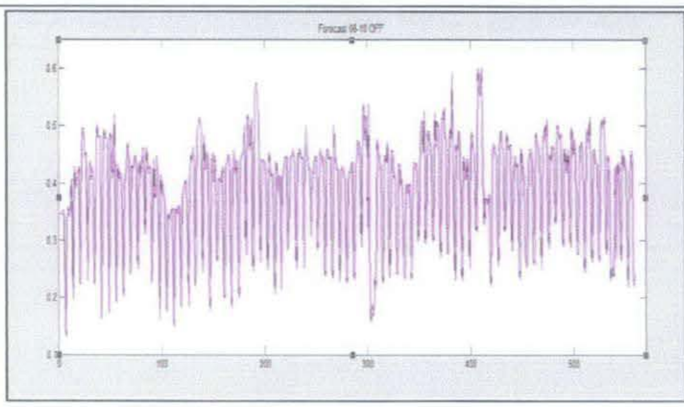
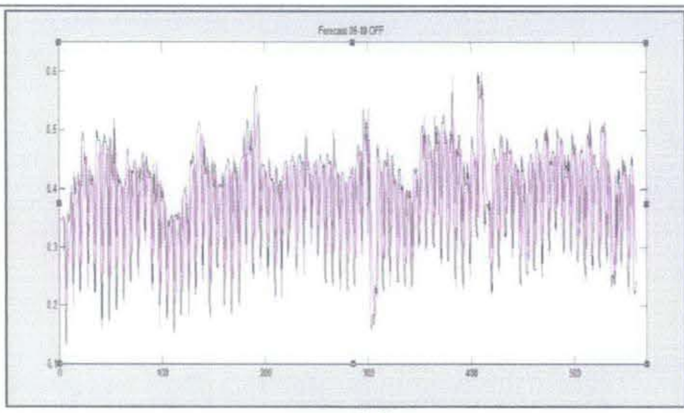
| Day | Load (MWatt) | Forecast Load (MWatt) |
|---|---|---|
| 1 | 4564 | 4565 |
| 2 | 4568 | 4466 |
| 3 | 4340 | 4359 |
| 4 | 4352 | 4337 |
| 5 | 4220 | 3321 |
| 6 | 1836 | 2391 |
| 7 | 2752 | 3003 |

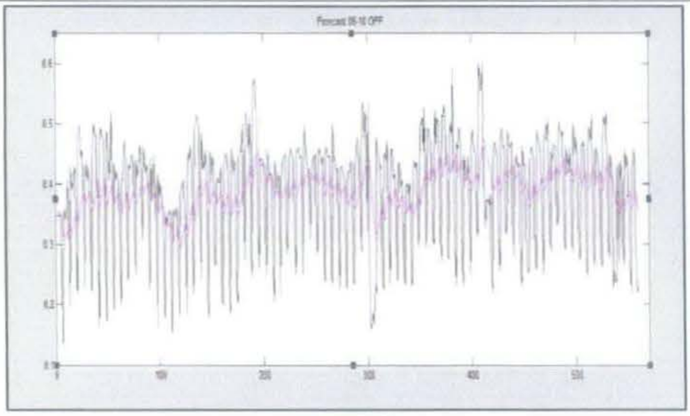
Therefore it can be concluded that to forecast the load for Semester ON 2011 to 2015, the alpha value should be equal to 0.3. In this case we are using exponential smoothing technique based on Semester OFF 2006-2010 raw data.

### 4.2.4 Semester OFF 2006-2010

For this part, we compare the behaviour of the graph plotted when we vary the alpha ($\alpha$) from 0 to 0.9. Notice that the raw data is plotted in black, while smoothed data is plotted in magenta.

Table 16: Forecast Load Semester OFF 2006-2010 with various $\alpha$.

| Graph Plot | Discussion |
|---|---|
|  $\alpha = 0$ | The plot of smoothed data is almost the same as the plot of raw actual data. In this case, alpha equal to 0 is not the best forecast model because of the exactness between actual value and forecasted value. |
|  $\alpha = 0.5$ | For this value of alpha, the plot of smoothed data obtained is lesser than actual plot. It will not be able to fulfil the next 5 years load demand thus not recommended. |

| | |
|---|---|
|  $\alpha = 0.9$ | In this case, the smoothed data plotted is absolutely smaller than the actual plot. The magenta line is more linear than the black line. Thus, we will not consider this plot. |

From the table above, when applied recursively to each successive observation in the series, each new smoothed value (forecast) is computed as the weighted average of the current observation and the previous smoothed observation. Thus, in effect, each smoothed value is the weighted average of the previous observations, where the weights decrease exponentially depending on the value of parameter $\alpha$ (alpha).

If $\alpha$ is equal to 1 (one) then the previous observations are ignored entirely; if $\alpha$ is equal to 0 (zero), then the current observation is ignored entirely, and the smoothed value consists entirely of the previous smoothed value (which in turn is computed from the smoothed observation before it, and so on; thus all smoothed values will be equal to the initial smoothed value). Values of $\alpha$ in-between will produce intermediate results.

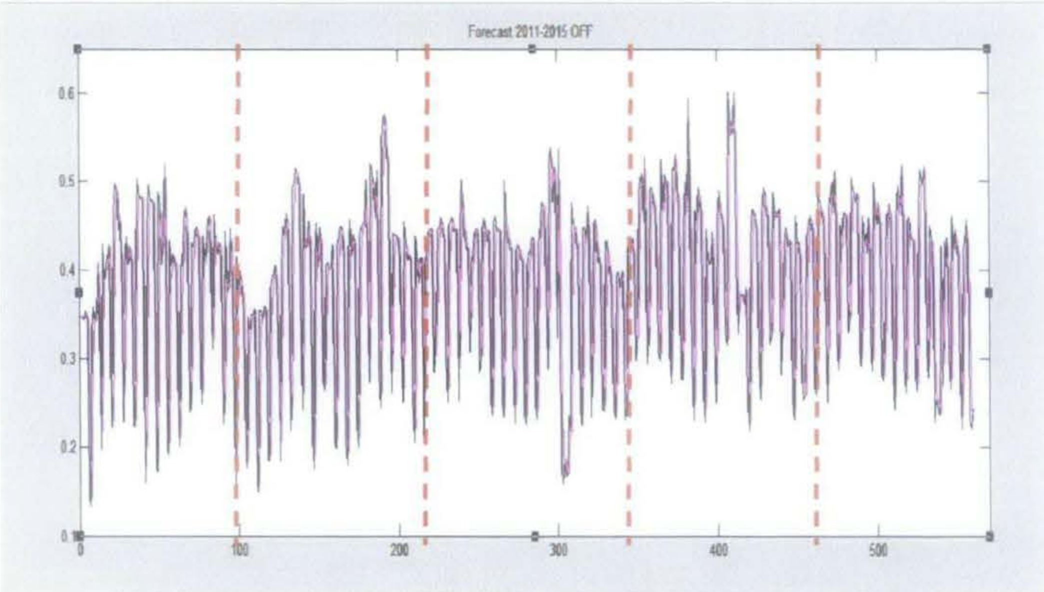



Figure 34: Forecast Load for Semester OFF 2006-2010 ($\alpha = 0.2$)

The graph above best load forecast value with minimal error. It is plotted when the value of alpha is 0.2. The plotted graph is smoothed with very little adjustment and it is more emphasis is on the actual data than on estimation capability.

There are five identical cycles from the graph above. We can analyze that the pattern of the graph which is almost the same when it is divided into five sections. It explains the load forecasted for the next five years will be in these patterns. The highest load is measured falls on about $400^{th}$ day which is about $0.6 \times 10^6$ MWatt while the lowest load is measured falls on about $5^{th}$ day which is about $0.15 \times 10^6$ MWatt.

For our forecasting, we have calculated and measured an error which is Mean Absolute Percentage Error (MAPE). As we increase the alpha value from 0 to 1 by increment of 0.1, we can see that the errors are also increase. This suggesting that the closer the alpha value to 0 will pick up more of the peaks and valleys associated with the historical demand, thus reducing the error. However, the least error will not indicate that it is the best forecasting model as we need to consider other criteria as well.

The summary of errors calculated is shown in the table below.

Table 17: Forecast Error Semester OFF 2006-2010 with various α.

| Alpha (α) | Mean Absolute Percentage Error (MAPE) (%) |
|---|---|
| 0 | 0 |
| 0.1 | 6.4102 |
| **0.2** | **13.6311** |
| 0.3 | 15.6683 |
| 0.4 | 18.3926 |
| 0.5 | 24.4939 |
| 0.6 | 33.5172 |
| 0.7 | 42.9938 |
| 0.8 | 52.4392 |
| 0.9 | 61.3653 |
| 1.0 | 57.9401 |

Below is the manual calculation of average value of forecast load when we are using α between range of 0.15 to 0.25 to prove that $\alpha = 0.2$ is the best .

Table 18: Calculation of forecast load ($0.15 < \alpha < 0.25$)

| Day | Load (MWatt) | Forecast Load (MWatt) |
|---|---|---|
| 1 | 3481 | 3478 |
| 2 | 3476 | 3467 |
| 3 | 3460 | 3507 |
| 4 | 3552 | 3493 |
| 5 | 3436 | 2885 |
| 6 | 2760 | 2448 |
| 7 | 1980 | 1695 |

Therefore it can be concluded that to forecast the load for Semester OFF 2011 to 2015, the alpha value should be equal to 0.2. In this case we are using exponential smoothing technique based on Semester OFF 2006-2010 raw data.

### 4.3 Result Using ARIMA Technique

"ARIMA(p,d,q)" model, where:

- p is the number of autoregressive terms,
- d is the number of integrated terms
- q is the number of moving average part

**Short Term Forecasting**

#### 4.3.1 Semester ON 2010

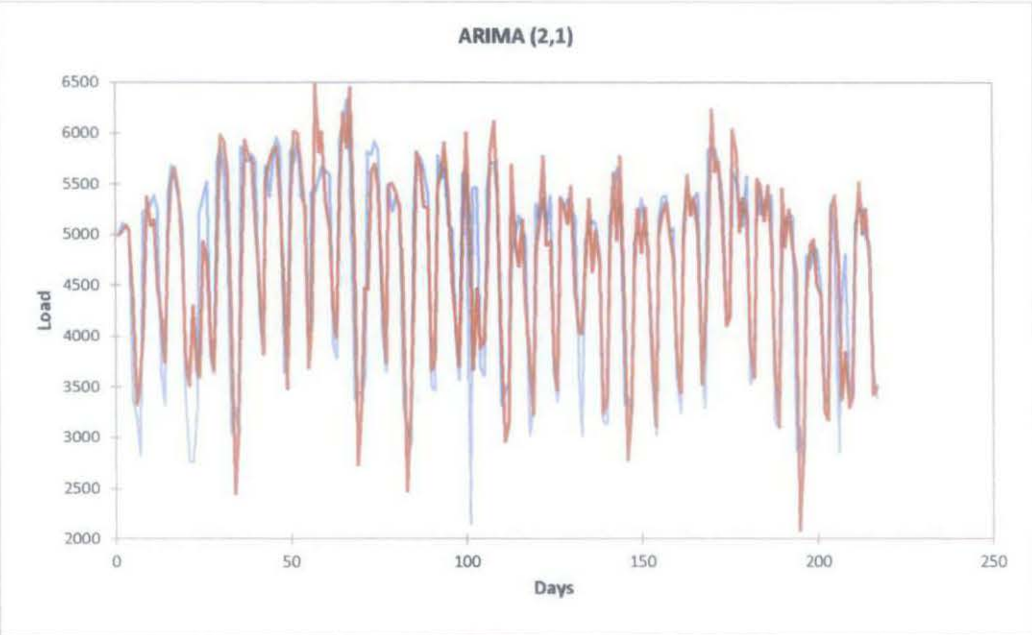



Figure 35: Forecast Load for Semester ON 2010 ARIMA(2,,1)

In this case, we use ARIMA technique with p = 2, d =1 and q = 0. The reason we use this value because it will produce much more accurate forecast. Note that the blue line is the actual load while the red curve is the forecast model.

### 4.3.2 Semester OFF 2010

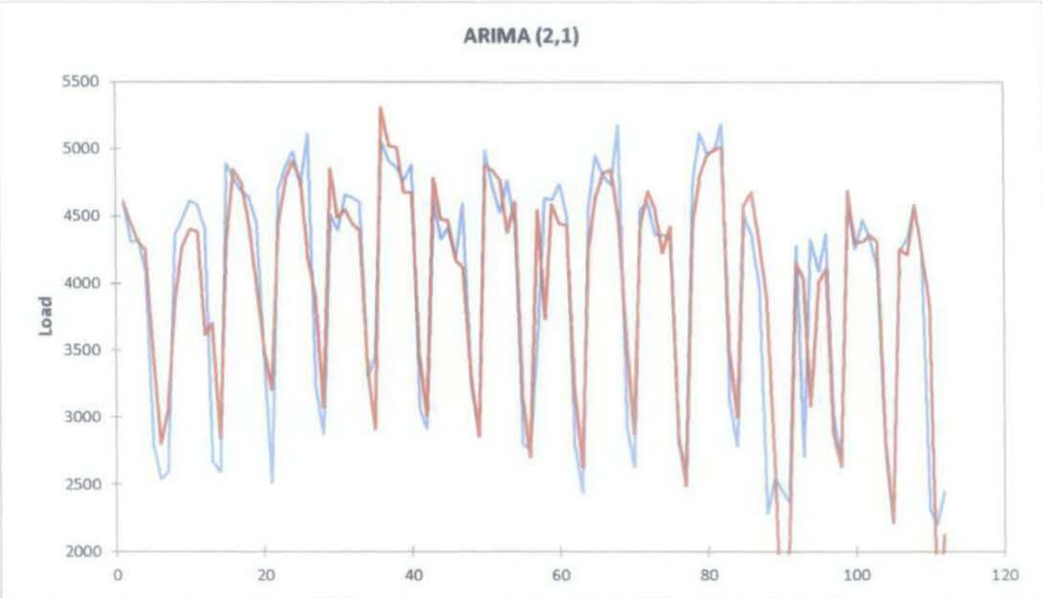



Figure 36: Forecast Load for Semester OFF 2010 ARIMA (2,1)

The same value can be applied to Semester OFF 2010 where we used p = 2, d =1 and q = 0. Note that the blue line is the actual load while the red curve is the forecast model.

**Long Term Forecasting**

### 4.3.3 Semester ON 2006-2010

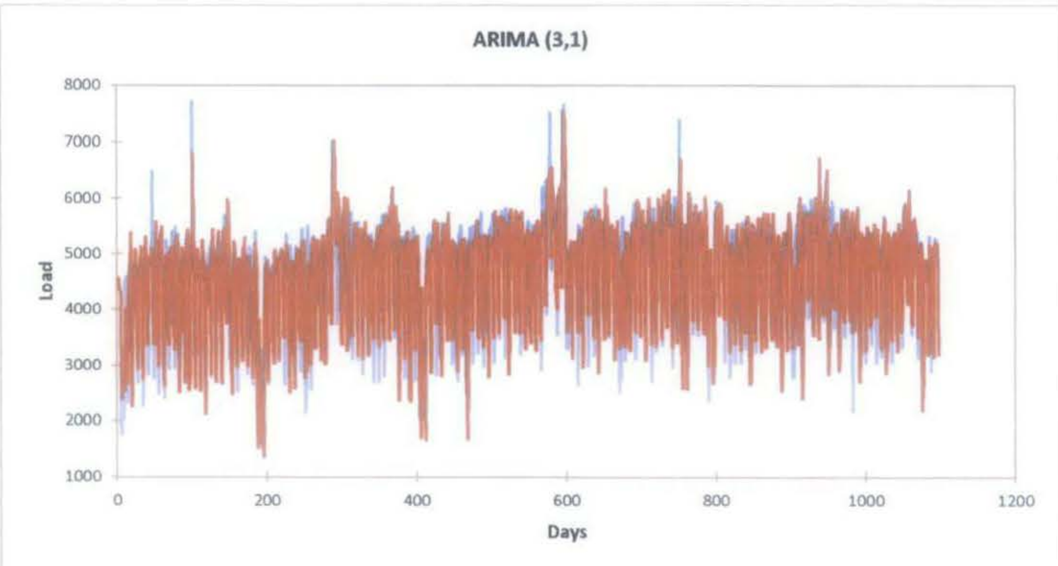



Figure 37: Forecast Load for Semester ON 2006-2010 ARIMA (3,1)

In this case, we use ARIMA technique with p = 3, d =1 and q = 0. The reason we use this value because it will produce much more accurate forecast. Note that the blue line is the actual load while the red curve is the forecast model.

### 4.3.4 Semester OFF 2006-2010

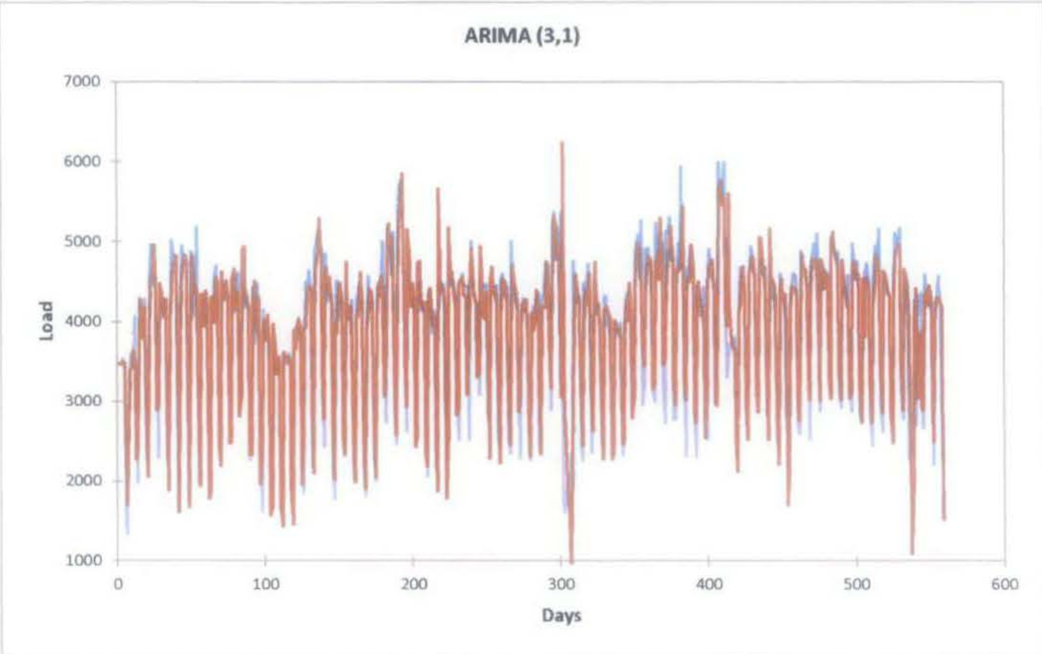



Figure 38: Forecast Load for Semester ON 2006-2010 ARIMA (3,1)

The same value can be applied to Semester OFF 2010 where we used p = 3, d =1 and q = 0. Note that the blue line is the actual load while the red line is the forecast model.

## 4.4 Comparison with Actual Load Data

### 4.4.1 Short Term Forecasting (Semester ON vs Semester OFF 2010)

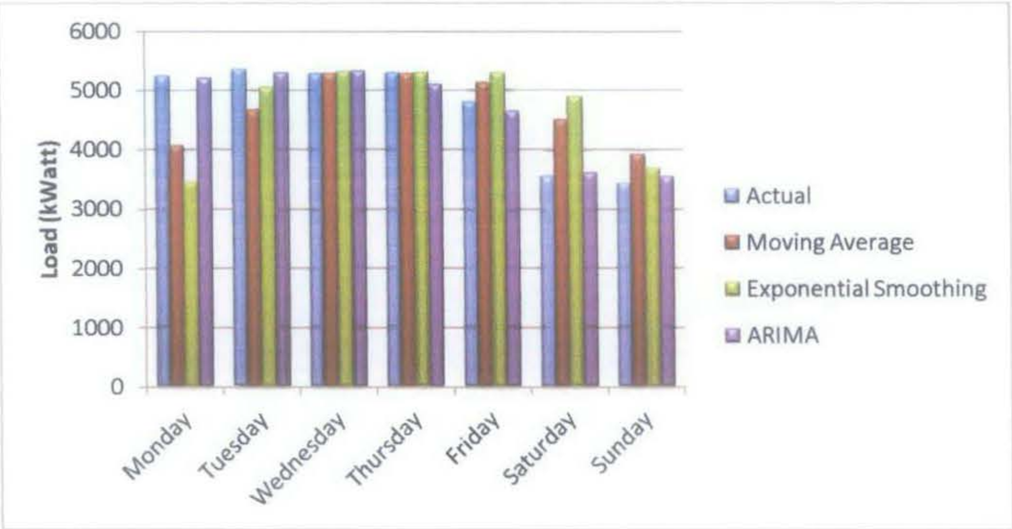



Figure 39: Comparison with Actual Load Semester ON 2010

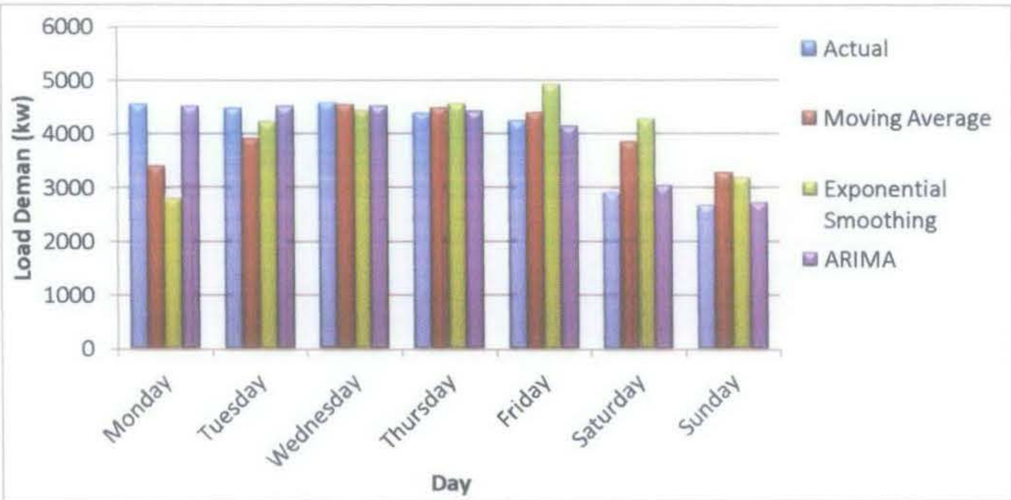



Figure 40: Comparison with Actual Load Semester OFF 2010

From Figure 39 and Figure 40, our observation is that by using ARIMA technique for forecast load, the result is very close to the actual value. Both moving average and exponential smoothing techniques does not meet the actual value correspondingly. The graphs also justify the lowest load will be on weekend than weekdays.

### 4.4.2 Long Term Forecasting (Semester ON vs Semester OFF 2006-2010)

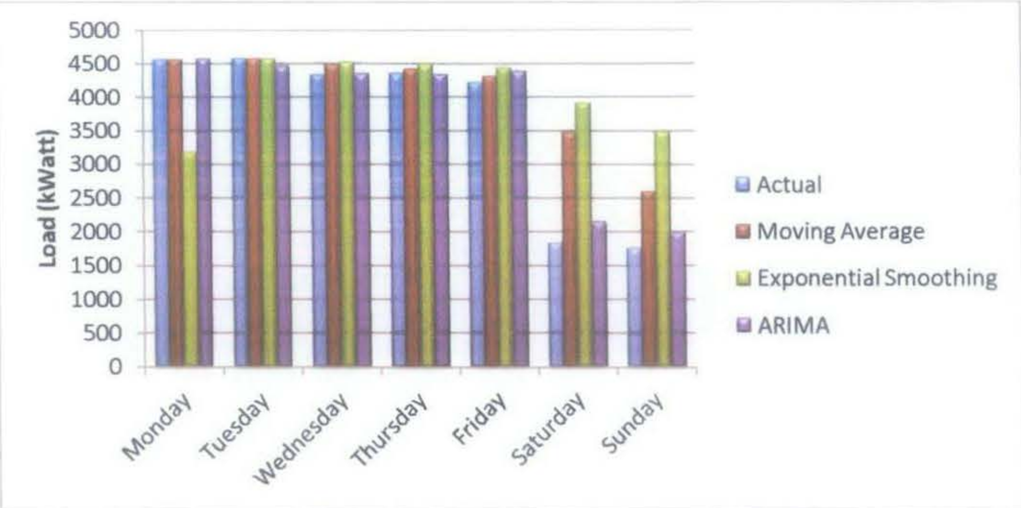



Figure 41: Comparison with Actual Load Semester ON 2006- 2010

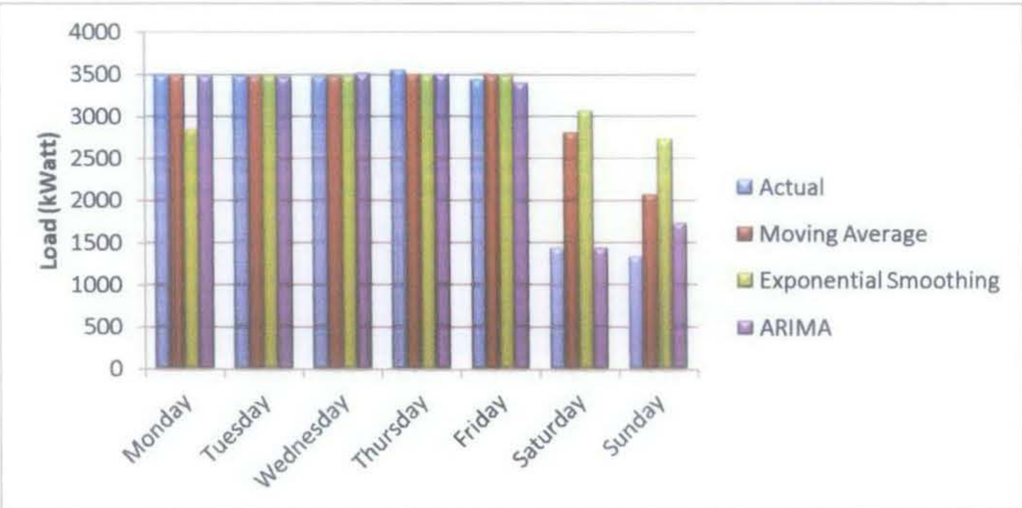



Figure 42: Comparison with Actual Load Semester OFF 2006- 2010

From Figure 41 and Figure 42, forecasting with ARIMA technique has the closest to the actual value than using moving average and exponential smoothing. However, on Sunday the value of ARIMA model slightly does not meet the standard due to extreme variation of data that we have.

# CHAPTER 5

# CONCLUSIONS AND RECOMMENDATIONS

For short term forecasting, the error calculate can be summarized as below

Table 19: MAPE for Short Term Forecasting (Semester ON vs Semester OFF)

| **Techniques** | **Semester ON (MAPE %)** | **Semester OFF (MAPE %)** |
|---|---|---|
| Moving Average | 18.07 | 17.06 |
| Exponential Smoothing | 12.99 | 14.43 |
| ARIMA | 7.64 | 8.74 |

For long term forecasting, the error calculate can be summarized as below

Table 20: MAPE for Long Term Forecasting (Semester ON vs Semester OFF)

| **Techniques** | **Semester ON (MAPE %)** | **Semester OFF (MAPE %)** |
|---|---|---|
| Moving Average | 19.87 | 21.76 |
| Exponential Smoothing | 14.43 | 13.63 |
| ARIMA | 9.34 | 7.89 |

Based on the results above, it can be concluded that both moving average and exponential smoothing does not produce satisfactory result. The MAPE calculate is higher than using ARIMA technique. ARIMA technique is more superior for short-term load forecasting as well as long term load forecasting. The model of ARIMA is an appropriate model to predict the future load trend, with a high prediction precision of short term time series.

As for recommendation, we can use hybrid method to obtain more accurate result with less error. For example we can combine ARIMA technique together with Artificial Neural Network or wavelets.

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| ACTIVITIES | FINAL YEAR PROJECT 1 | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | WEEK NO. | | | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| Choose Topic | | | | | | | | | | | | | | |
| Study the topic | | | | | | | | | | | | | | |
| Literature Review | | | | | | | | | | | | | | |
| Extended Proposal | | | | | | 0 | | | | | | | | |
| Run and Analyze the simulation based on example | | | | | | | | | | | | | | |
| Gather Data from GDC UTP | | | | | | | | | | | | | | |
| Study and analyze data | | | | | | | | | | | | | | |
| Draft Report | | | | | | | | | | | | | 0 | |
| Interim Report | | | | | | | | | | | | | | 0 |
| Design and develop forecast model | | | | | | | | | | | | | | |

APPENDIX A

GANTT CHART

| ACTIVITIES | FINAL YEAR PROJECT 2 | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | WEEK NO. | | | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| New progress for FYP1 | | | | | | | | | | | | | | |
| Progress Report | | | | | | | | 0 | | | | | | |
| Final Results / Findings | | | | | | | | | | | | | | |
| Pre - Edx | | | | | | | | | | | 0 | | | |
| Draft Report | | | | | | | | | | | | 0 | | |
| Final Report | | | | | | | | | | | | | 0 | |
| Viva | | | | | | | | | | | | | | |
| Technical Report Submission | | | | | | | | | | | | | | 0 |

APPENDIX A

GANTT CHART

# APPENDIX B

# UTP ACADEMIC CALENDAR

**Semester ON 2010**

| JAN 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 25-Jan-10 | 12-Mar-10 | Day 1 – Day 43 |
| Lecture | 7 | 22-Mar-10 | 7-May-10 | Day 44 – Day 87 |
| Study Week | 1 | 8-May-10 | 16-May-10 | Day 88 – Day 94 |
| Examination Week | 3 | 17-May-10 | 4-Jun-10 | Day 95 – Day 109 |

| JULY 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 26-Jul-10 | 3-Sep-10 | Day 110 – Day 153 |
| Lecture | 7 | 15-Sep-10 | 5-Nov-10 | Day 154 – Day 197 |
| Study Week | 1 | 6-Nov-10 | 14-Nov-10 | Day 198 – Day 204 |
| Examination Week | 3 | 15-Nov-10 | 3-Dec-10 | Day 205 – Day 218 |

**Semester OFF 2010**

| JAN 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 13-Mar-10 | 21-Mar-10 | Day 1 – Day 9 |
| End of Semester Break | 7 | 5-Jun-10 | 25-Jul-10 | Day 10 – Day 58 |

| JULY 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 4-Sep-10 | 14-Sep-10 | Day 59 – Day 67 |
| End of Semester Break | 7 | 4-Dec-10 | 23-Jan-11 | Day 68 – Day 116 |

**Semester ON 2006 -2010**

| JAN 2006 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 23-Jan-06 | 10-Mar-06 | Day 1 – Day 44 |
| Lecture | 7 | 20-Mar-06 | 5-May-06 | Day 45 – Day 88 |
| Study Week | 1 | 6-May-06 | 14-May-06 | Day 89 – Day 95 |
| Examination Week | 3 | 15-May-06 | 2-Jun-06 | Day 96 – Day 110 |

| JULY 2006 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 24-Jul-06 | 8-Sep-06 | Day 111 – Day 159 |
| Lecture | 7 | 18-Sep-06 | 3-Nov-06 | Day 160 – Day 203 |
| Study Week | 1 | 4-Nov-06 | 12-Nov-06 | Day 204 – Day 210 |
| Examination Week | 3 | 13-Nov-06 | 1-Dec-06 | Day 211 – Day 225 |

| JAN 2007 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 22-Jan-07 | 9-Mar-07 | Day 226 – Day 269 |
| Lecture | 7 | 19-Mar-07 | 4-May-07 | Day 270 – Day 313 |
| Study Week | 1 | 5-May-07 | 13-May-07 | Day 314 – Day 320 |
| Examination Week | 3 | 14-May-07 | 1-Jun-07 | Day 321 – Day 335 |

| JULY 2007 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 23-Jul-07 | 7-Sep-07 | Day 336 – Day 379 |
| Lecture | 7 | 17-Sep-07 | 2-Nov-07 | Day 480 – Day 423 |
| Study Week | 1 | 3-Nov-07 | 11-Nov-07 | Day 424 – Day 430 |
| Examination Week | 3 | 12-Nov-07 | 30-Nov-07 | Day 431 – Day 445 |

| JAN 2008 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 21-Jan-08 | 7-Mar-08 | Day 446 – Day 489 |
| Lecture | 7 | 17-Mar-08 | 2-May-08 | Day 490 – Day 533 |
| Study Week | 1 | 3-May-08 | 11-May-08 | Day 534 – Day 540 |
| Examination Week | 3 | 12-May-08 | 30-May-08 | Day 541 – Day 555 |

| JULY 2008 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 21-Jul-08 | 26-Sep-08 | Day 556 – Day 599 |
| Lecture | 7 | 8-Oct-08 | 31-Oct-08 | Day 600 – Day 643 |
| Study Week | 1 | 1-Nov-08 | 9-Nov-08 | Day 644 – Day 650 |
| Examination Week | 3 | 10-Nov-08 | 28-Nov-08 | Day 651 – Day 665 |

| JAN 2009 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 19-Jan-09 | 20-Mar-09 | Day 666 – Day 709 |
| Lecture | 7 | 30-Mar-09 | 1-May-09 | Day 710 – Day 753 |
| Study Week | 1 | 2-May-09 | 10-May-09 | Day 754 – Day 760 |
| Examination Week | 3 | 11-May-09 | 29-May-09 | Day 761 – Day 775 |

| JULY 2009 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 20-Jul-09 | 18-Sep-09 | Day 776 – Day 819 |
| Lecture | 7 | 30-Sep-09 | 30-Oct-09 | Day 820 – Day 863 |
| Study Week | 1 | 31-Oct-09 | 8-Nov-09 | Day 864 – Day 870 |
| Examination Week | 3 | 9-Nov-09 | 27-Nov-09 | Day 871 – Day 885 |

| JAN 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 25-Jan-10 | 12-Mar-10 | Day 886 – Day 929 |
| Lecture | 7 | 22-Mar-10 | 7-May-10 | Day 930 – Day 973 |
| Study Week | 1 | 8-May-10 | 16-May-10 | Day 974 – Day 980 |
| Examination Week | 3 | 17-May-10 | 4-Jun-10 | Day 981 – Day 995 |

| JULY 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Lecture | 7 | 26-Jul-10 | 3-Sep-10 | Day 996 – Day 1039 |
| Lecture | 7 | 15-Sep-10 | 5-Nov-10 | Day 1040 – Day 1083 |
| Study Week | 1 | 6-Nov-10 | 14-Nov-10 | Day 1084 – Day 1090 |
| Examination Week | 3 | 15-Nov-10 | 3-Dec-10 | Day 1091 – Day 1105 |

**Semester OFF 2006-2010**

| JAN 2006 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 11-Mar-06 | 19-Mar-06 | Day 1 – Day 8 |
| End of Semester Break | 7 | 3-Jun-06 | 23-Jul-06 | Day 9 – Day 56 |

| JULY 2006 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 9-Sep-06 | 17-Sep-06 | Day 57 – Day 64 |
| End of Semester Break | 7 | 2-Dec-06 | 21-Jan-07 | Day 65 – Day 112 |

| JAN 2007 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 10-Mar-07 | 18-Mar-07 | Day 113 – Day 120 |
| End of Semester Break | 7 | 2-Jun-07 | 22-Jul-07 | Day 121 – Day 168 |

| JULY 2007 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 8-Sep-07 | 16-Sep-07 | Day 169 – Day 176 |
| End of Semester Break | 7 | 1-Dec-07 | 20-Jan-08 | Day 177 – Day 224 |

| JAN 2008 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 8-Mar-08 | 16-Mar-08 | Day 225 – Day 232 |
| End of Semester Break | 7 | 31-May-08 | 20-Jul-08 | Day 233 – Day 280 |

| JULY 2008 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 27-Sep-08 | 7-Oct-08 | Day 281 – Day 288 |
| End of Semester Break | 7 | 29-Nov-08 | 18-Jan-09 | Day 289 – Day 336 |

| JAN 2009 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 21-Mar-09 | 29-Mar-09 | Day 337 – Day 344 |
| End of Semester Break | 7 | 30-May-09 | 19-Jul-09 | Day 345 – Day 392 |

| JULY 2009 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 19-Sep-09 | 29-Sep-09 | Day 393 – Day 400 |
| End of Semester Break | 7 | 28-Nov-09 | 17-Jan-10 | Day 401 – Day 448 |

| JAN 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 13-Mar-10 | 21-Mar-10 | Day 449 – Day 456 |
| End of Semester Break | 7 | 5-Jun-10 | 25-Jul-10 | Day 457 – Day 504 |

| JULY 2010 SEMESTER | | | | |
|---|---|---|---|---|
| PARTICULAR | NO. OF WEEKS | DATE | | DAY |
| | | START | ENDS | |
| Mid-Semester Break | 1 | 4-Sep-10 | 14-Sep-10 | Day 505 – Day 512 |
| End of Semester Break | 7 | 4-Dec-10 | 23-Jan-11 | Day 513 – Day 560 |