GAS DISTRICT COOLING LOAD DEMAND MODELLING

By

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CERTIFICATION OF APPROVAL

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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.

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Muhamad Fahmi Bin Mohd Yusoff

ABSTRACT

Gas District Cooling (GDC) is a co-generation plant that owned by Universiti Teknologi PETRONAS (UTP). The plant supplies electricity and chilled water to the UTP campus. At present, there is no mathematical model available for GDC application. As a sole customer of the plant, the UTP 2011 load demand data is used to develop the load demand modelling using exponential smoothing methods. The methods produce a few mathematical models that replicate UTP 2011 load demand pattern. The result obtain in the analysis would address the variation of electricity demand in the university which is beneficial for the utility company and for forecasting purpose. Winter's method is selected to characterize the mathematical load demand modelling for UTP since it produced the lowest MAPE as compared to Simple, Holt's Fit and Holt-Winters of exponential smoothing methods.

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LIST OF ABBREVIATION

UTP	Universiti Teknologi PETRONAS
GDC	Gas District Cooling
ANN	Artificial Neural Network
HW	Holt Winters
AR	Autoregressive
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving-Average
ARMAX	Autoregressive Moving Average with Exogenous Variable

CHAPTER 1
INTRODUCTION

1.1 Background of Study

An electrical load forecast is crucial for efficient management of power system for a power station. It is necessity in order to optimize and to reduce the cost of electric energy consumption. Furthermore, ability to form a mathematic model of historical data of the forecast object is the pitch of a load forecast. It will determine the accuracy of the forecast load. For Universiti Teknologi PETRONAS (UTP), Gas District Cooling (GDC) is the main power plant. GDC is capable to generate up to 8.4MW of electrical power [1,2]. For this project, there are two main objectives that would be realized in this report. The first one is to analyse and study the load demand behaviours of UTP while the second one is to formulate the mathematical model that can represent the load demand behaviours of UTP.

1.2 Problem Statement

1.2.1 Problem Identification

There are various methods available to make a mathematical model of the load demand. In [3], there are nine methods of forecasting that have been classified which include exponential smoothing, stochastic time series, fuzzy logic, and neural networks. Thus, in order to obtain the best and accurate model for developing a mathematical model, studies need to be done in order to choose the best method.

Due to the need for an analysis of the historical load demand data of the previous one, there must be enough data to conduct the required analysis. For that purpose, historical UTP load demand data for the year of 2011 which started on 1st January 2011 until 31 December 2011 have been gathered from GDC. This load demand profile has been chosen as the study period. Besides, important events throughout the year of 2011 which include holiday, festivals, events in UTP and academic schedules of UTP are gathered for the analysis purposes. This information is collected from the 2011 Malaysia calendar, academic calendar, tripping record of GDC, UTP Registrar Department and UTP Maintenance Department.

1.2.2 Significant of Project

Mathematical load demand model plays an important role for forecasting purposes and aids in the determination of load demand forecast accuracy. A more accurate result would save hundreds of thousands dollar to the electric utility company since the load forecast would be used for operation and planning, fuel allocation, system expansion and optimization of network development of the company [5].

1.3 Objective and Scope of the project

1.3.1 Main Objective

The objectives of the project are as follows:

1. To analyse and study the load demand behaviour of UTP.
2. To formulate the mathematical model that can represent the load demand behaviour of UTP.

1.3.2 Scope of Project

This project will start with some literature review related to load forecasting and mathematical modelling. Next, there will be load demand data gathering from GDC UTP which is the case study. The aim is to get the best approximate equation that can replicate the load demand profile of the study period. Besides, there will be series of fine tuning process to improve the accuracy of the mathematical models develop to the best. Then, the project will continue with next stages of mathematical model development or other methods that are suitable.

1.4 Relevancy of Project

This project is done from the load demand data that is available at the Gas District Cooling (GDC) of Universiti Teknologi PETRONAS. Currently, there is no mathematical model available for GDC application. The mathematical model developed, can be used by the GDC in assisting the forecast project to predict the future load demand in UTP. Besides, GDC also can use this model to analyses the load demand behaviours in Universiti Teknologi PETRONAS to assist in operation and planning purposes of their power plant.

1.5 Feasibility of Project

This project will be done in two semesters which include research, data gathering, analysing and model formulation. For research part, information regarding mathematical modelling are gather from related journal, conference proceeding and books during the first semester. MATLAB, MINITAB and Microsoft Excel software are available and will be used as the tools to formulate the mathematical model of the GDC load demand. Additionally, a preliminary mathematical model would be constructed in the first semester and the model would be optimized and finalized during the second semester. Based on the Gantt chart developed, it is confidently assured that this project can be carried out within the time frame given.

CHAPTER 2
LITERATURE REVIEW

Over the decade, there have been several methods varying in complexity of functional form and estimation procedures that have been proposed for producing a mathematical model and forecast result [3]. Mathematical model and forecasting have a mutual relationship since the mathematical model will determine the result of a forecasting process. There will be mathematical modelling done first before a forecasting process takes place for most cases. In this literature review, I will list most of the methods and some explanation pretending to the methods.

2.1 Exponential Smoothing

Exponential smoothing is a statistical method for doing a load forecasting [3,5,6]. This method is based on the time series and would take into consideration of historical data in order to establish a pattern in the past that resembles or similar to current load curve [7]. Exponential smoothing also would be used for generating smoothed values of the data and later obtain the best estimation [8]. This exponential smoothing method would perform best when the time series is stationary and the consumption is similar to recent past. If this condition is not achieved, exponential smoothing would give poor forecast result compare to the fitting techniques such as linear regression, fuzzy and neural network [3,9]. Despite the statement made by [3,9] of the performance of exponential smoothing method a conclusion must not be made directly since currently this method has been improved and put into some variation onward. The types of exponential smoothing that currently use are listed below:

i. Simple Exponential Smoothing
ii. Exponential Smoothing with Trend (Holt's Fit)
iii. Exponential Smoothing with Seasonality (Winter's method)
iv. Holt-Winters Exponential Smoothing

A newer research [10] has compare three methods of forecasting which are Seasonal ARMA Modelling, Periodic AR Models and Double Seasonal Holt-Winters Exponential Smoothing based on European data has found that the methods that consistently performed best is Holt-Winters Exponential Smoothing. Furthermore, in [11] a comparative study has been done to compare ARIMA model, Neural Network Model and Exponential Smoothing with Double Seasonality has found that the result achieve by ARIMA model are more satisfactory compare to neural network but the best was exponential smoothing model with double seasonality. Besides, in [12], it is states that exponential smoothing has produce a satisfactory result at a very reasonable cost and therefore it is use by lots of company.

2.1.1 Simple exponential smoothing

Simple exponential smoothing or first-order exponential smoothing is usually used for short-range forecasting, usually just for a month into the future. This model is use when the data fluctuates around a reasonably stable means with no trend or consistent pattern found [13]. However, if the data does shows pattern or trend in the load profile, simple exponential smoothing will also be develop and it will be the base model for the next stages of exponential smoothing likes Holt's Fit and Winter's Method. Simple exponential smoothing uses a recursive equation which can be translate as a linear combination of the current observation and smoothed observation of the previous time unit [8]. The specific formula for simple exponential smoothing is given in equation 1 as:

$$y_{t+1} = \alpha . x_t + (1 - \alpha) y_t \qquad (1)$$

Where;

y_{t+1} is the estimated value for moment t+1

x_t is the real value for moment t

α discount factor of range from 0 to 1

From the equation, the discount factor alpha (α) represents the weight to put into the previous observation while (1- α) is the weight put on the smoothed value of the previous observations. Alpha (α) is the most important issues for the exponential smoothing method [8]. The initial value of y_{t+1} plays an important role in computing all the subsequent values. There are two ways to apply. The first one is to use the first observation data while the second one is to take average of the first four or five observation. The smaller the value of alpha (α), the more important the selection of initial value of y_{t+1} would be [13].

2.1.2 *Exponential Smoothing with Trend (Holt's Fit)*

This method is use when the data shows a trend [8,6,14]. It work just like the first-order exponential smoothing only that there are two component that need to be updated in each period which are level and trend. Level represent the smoothed estimate of the value of the data at the end of each period while trend is the trend estimate of average growth at the end of each period [13]. The specific formula for Holt's Fit is given in equation 2 and 3:

$$y_{t+1} = \alpha . x_t + (1-\alpha).(y_{t-1} + T_{t-1}) \qquad 0 < \alpha < 1 \qquad (2)$$

$$T_{t+1} = \beta(y_{t+1} - y_t) + (1-\beta).(T_t) \qquad 0 < \beta < 1 \qquad (3)$$

Where;

α,β [0,1] are the discount factors (constant)

x_t is the real value for moment t

y_t is the forecast value

T_t value of trend

The current value in the series would be used to calculate its smoothed value replacement in double exponential smoothing. The initial value for y_t is set to be the value of first observation data while for T_t there are three suggestions for T_1 [13] :

$$T_1 = y_2 - y_1 \qquad (4)$$

$$T_1 = (y_n - y_1)/(n-1) \qquad (5)$$

$$T_1 = [(y_2 - y_1) + [(y_3 - y_2) + [(y_4 - y_3)]/3 \qquad (6)$$

2.1.3 *Exponential Smoothing with Seasonality (Winter's method)*

Winter's Method is use when the load demand data have seasonality, but no trend [13,15]. It works just like the first-order exponential smoothing only that there are seasonal index to be included. The number of seasons and seasonal indices vary from case to case and is depending on the load demand data pattern. The total of all seasonality should be equal to the number of seasons [15]. The specific formula for Winter's Method is given in equation 7 as:

$$y_{t+1} = [\alpha.x_t + (1-\alpha)y_t]\gamma \tag{7}$$

Where;

y_{t+1} is the estimated value for moment t+1

x_t is the real value for moment t

α discount factor of range from 0 to 1

γ Seasonal index

2.1.4 The Holt Winters (HW) Exponential Smoothing.

Holt Winters exponential smoothing is named after its inventor. This method is use when the data shows trend and seasonality [13,15]. There are three estimates for Holt-Winters exponential smoothing method; one for the smoothed value, the second for trend and the third for seasonality. The specific formulas for second order exponential smoothing are given in equation 8 and 9 as:

$$y_{t+1} = [\alpha.x_t + (1-\alpha).(y_{t-1} + T_{t-1})]\gamma \tag{8}$$

$$T_{t+1} = \beta(y_{t+1} - y_t) + (1-\beta).(T_t) \tag{9}$$

Where

α,β [0,1] are the discount factors (constant)

x_t is the real value for moment t

y_t is the forecast value

T_t value of trend

γ seasonal index

2.2 Stochastic Time Series

This method is use when a unique pattern of energy and demand pertaining to fast growing areas are difficult to be analysed by direct application of time series method. Thus, stochastic time series approach is introduced. This method would first develop a pioneer model based on previous data then based on this model a future load is predicted. This approach is the most popular approach for a short term load forecast [3].

2.2.1 Autoregressive (AR) Model

Autoregressive (AR) model is used when the load is to be a linear combination of previous load. The equation given by [15] for autoregressive AR model is given in equation 10:

$$L_k = -\sum_{i=1}^{m} \alpha_{ik} L_{k-i} + w_k \tag{10}$$

Where;

L_k predicted load at time k (min)

w_k random load disturbance

α_{ik} unknown coefficient

The unknown coefficient can be tune using least means square (LMS) algorithm of [16].

2.2.2 Autoregressive moving average (ARMA) model

In ARMA model, the current value of time series y(t) is expressed linearly in terms of its values at previous period and previous white noise [3]. For ARMA of order (p,q), the model is written as in equation 11 which is:

$$y(t) = \emptyset_1 y(t-1) + \cdots + \emptyset_p y(t-p) + a(t) - \emptyset_1 a(t-1) - \cdots - \emptyset_q a(t-q) \tag{11}$$

Where;

$y(t-1)$ value of previous period

$a(t-1)$ value of previous white noise

By using non-linear regression algorithm, the parameter for ARMA model can be determined.

2.2.3 Autoregressive Integrated Moving-Average (ARIMA) model

ARIMA model utilize a stationary form of a series. Thus, for a non-stationary process, a transformation to stationary form is needed. A process called differencing process can be used [3]. Then, the autocorrelation and partial autocorrelation function and the application of the Augmented Dickey-Fuller test are used to confirm the obtained differenced series is a stationary one [12].

2.3 Multiple Regression

This method uses the technique of weighted least-squares estimation. From this estimation, a statistical relationship between the parameter involves such as load, weather condition and the day type influences will be made. The regression coefficients are computed by an equally or exponentially weighted least squares estimation using the available data [3] [17,1]. The multiple regression model as in [19] is given in equation 12 which is:

$$Y_t = v_{t+}a_t + \in_t \tag{12}$$

Where;

Y_t measured system total load

v_t vector of adapted variables such as time, temperature, light intensity, wind speed, humidity, day type, etc.

a_t trasport factor of regression coefficient

$\in_t$ model error at time t.

The number of parameter involve for the multiple regression analysis is depending on availability of data. For example, in order to precisely improve the forecasting in Irish electricity, [19] has presented the weather-load model. In order to do so, regression analysis is done for historical load and weather data. From the data, the components that are influence and not sensitive to the weather are determined. These two parameters then are added to the model as parameters involved. The examples of parameter that can be included are holiday, day type, season, weather, solar radiation, population, income per capita and size of neighbourhoods [3] [20] [21] [9].

2.4 Iterative Reweighted Least-Squares

The model order and parameter for iterative reweighted least squares is determined by a method that utilizes autocorrelation and partial autocorrelation function which is based on resulting differenced past load data. It is done so to identify a sub-optimal model of the dynamic load [3]. In others word, this method would control one variable at a time, then the model order and its parameter would be determined. The iterative reweighted least squares equation based on [3] is given in equation 13:

$$Y = XB + \in \tag{13}$$

Where;

Y n x 1 vector of observation

X n x p matrix of known coefficients based on previous load data

B p x 1 vector of unknown parameter

$\in$ n x 1 vector of random error

The initial value of B can be determined by using the Newton law or Beaton-Turkey iterative reweighted least squares algorithm (IRLS). Based on [22] the result would be more accurate if the error obtains is not Gaussian.

2.5 Adaptive Load Forecasting

This method is called adaptive since the model is auto correct to cope with changing load condition. Adaptive load forecasting would require an online software package in the utility control system. Based on Kalman filter theory, a regression analysis is done to estimate the next state vector. Usually Kalman filter would use current prediction error as well as current weather data acquisition in order to estimate the next state vector. The total historical data set is analyzed to determine the next state vector without rely only to the most recent measured load and weather data. This model would use the same equation as multiple regressions as in 2.3 sections which is:

$$Y_t = v_{t+}a_t + \in_t \tag{14}$$

2.6 ARMAX model based on genetic algorithm

In identifying the ARMAX model, a genetic algorithm (GA) or evolution programming (EP) would be used. Then, a simulation of natural evolutionary process is done and the algorithm will be able to bring the data towards the global extremum of a complex error surface. GA simulation would evaluates many points in the search space and need not assume the search space is differential able or unimodel thus would improve the fitting accuracy of the model later [3].

2.7 Fuzzy Logic

Fuzzy logic system with centroid defuzzification can identify and approximate any unknown dynamic system (load) on the compact set to arbitrary accuracy [3]. It has the capability in drawing the similarity of a huge data [15]. Fuzzy logic forecast works in two stages which are training and on line forecasting [1]. During the training phase, the historical load data are used to 2m-input, 2n-output fuzzy logic based forecaster to generate a pattern database by using first and second order differences of data. After the training, it will be linked to a controller which then would predict the most probably matching pattern with the highest possibility that are found. Then, an output pattern would be generated by centroid defuzzifier.

2.8 Neural Network

Neural networks are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task [23]. It has a very wide application because of its ability to learn [3,2,5]. ANN traces previous load data pattern and extrapolates a load pattern using recent load data [24]. This method would not need a load model but incorporate of load historical into training process that consume lots of time. Their basic unit is the artificial neuron. The neuron receives (numerical) information through a number of input nodes processes it internally, and puts out a response [25].Before getting the output response, the information will be passed through a transfer function which is linear, sigmoid or hyperbolic tangent. The basic building blocks of the ANN are such as Network Architecture (connection between neurons), Training or Learning (determining weights on the connections) and Activation function.

2.9 Knowledge-based expert system

This is a new method that emerges as a result of advances in the field of artificial intelligence. This method has the ability to reason, explain, and have its knowledge base expanded as new information become available to it. In building the model, the knowledge engineer would extract load forecasting knowledge from the expert in forecasting field. This is called as the knowledge base component of the expert system. This knowledge is represent as a set of IF-THEN rules and consist of a relationships between the changes in the system load and changes in natural and forced condition factor that affect the use of electricity. This rule base is use daily to generate the load forecast. There are rule that need constant update while some will just remain unchanged [3].

CHAPTER 3
METHODOLOGY

3.1 Research Methodology

In order to successfully complete this project and achieve the objectives that have been planned, a thorough research and has been conduct in the early phase of this project. This research is done in order to obtain a strong foundation about this mathematical modelling, realise the difficulties, learn from the expert and learn lots more other important aspects needed to make sure that this project would be successful.

Literature reviews and brief research about mathematical modelling and forecasting are carried through sources such as journals, books, and the internet. However, the main source of this project comes from journals that obtain from a reputable source such as IEEE Journal and International Journal of System Science. Besides, a comparative studies among the journal collected also has been done in order to make sure the information obtain is supported by the others and latest journal is given higher priority during the process.

Then, data from Gas District Cooling (GDC) would be gathered and be analysed. The analysis is done according to the research in the literature and important information such as the holiday break and GDC tripping occurrence that have been collected earlier. This information is collected from the 2011 Malaysia Calendar, UTP 2011 Academic Calendar, tripping record of GDC, UTP Registrar Department and UTP Maintenance Department. Finally, based on the analysis, the mathematical models for the load demand profile in Universiti Teknologi PETRONAS will be developed.

3.2 Flow Chart

The methodology in executing this project can also be described using the flow chart as shown in Figure 1:

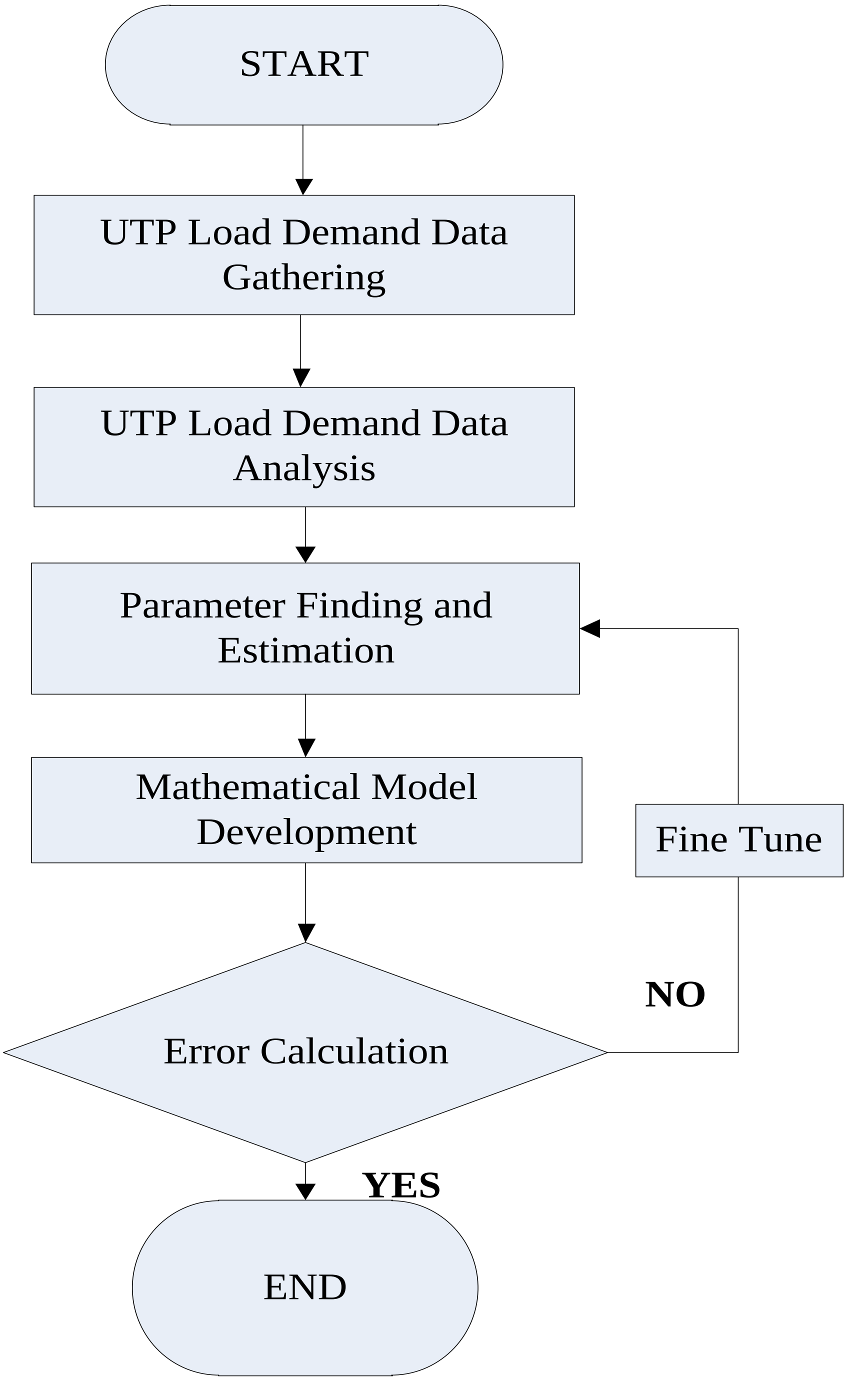

Figure 1 Flow Chart

3.2.1 Literature Review

An in deep research and literature review is done in order to gain knowledge and information regarding mathematical modelling. This research would enable us to determine the feasibility of the method available and finalize the method for developing the mathematical model. Literature reviews are obtained from a reputable source such as IEEE Journal and International Journal of System Science. Besides, a comparative studies among the journal collected also has been done in order to make sure the information obtain is supported by the others and latest journal is given higher priority during the process.

3.2.2 GDC Load Demand Data Gathering

The load demand data for year 2011 was collected from the Gas District Cooling (GDC). This load demand data is the representations of maximum load that occur for each day in a year. This load demand data then sorted in weekly basis to see the pattern of load demand for each day. Then, by referring to the 2011 Malaysian calendar, UTP 2011 academic calendar the holiday is highlighted to differentiate between lecture days, holiday load demand and special event such as study week, examination week and trip. A copy of this load demand data table can be found in Appendix A.

3.2.3 Mathematical Model Selection

Currently there are nine method of mathematical modelling to be chose from which are exponential smoothing, stochastic time series, multiple regression, iterative reweighted least squares, adaptive load forecasting, ARMAX model based on genetic algorithm, fuzzy logic, neural network and knowledge based expert system. These methods vary from their complexity of functional form and estimation procedures that have been proposed for producing a mathematical model. Based on the literatures that have been done, the exponential smoothing has a credibility to give a good equation for the load demand data as discussed before in literature review section. Thus, this method will be the chosen method in our mathematical model development.

3.2.4 Parameters Finding and Estimation

After the method is chosen, the parameters for developing the mathematical model is determine. There are four types of exponential smoothing that would be used for developing the GDC load demand mathematical models which are Simple Method, Holt's Fit, Winter's Method and Holt-Winter Method. First step to develop a mathematical model is to initially guess some of initial parameters. Ones example of them is the initial value of forecast. According to [13] there are two methods to set the initial load demand forecast (y_t). First is by setting the initial load demand forecast (y_t) value equal to the exact initial load demand (X_1). While, the second ones is by taking average of five consecutive readings of load demand for the initial load forecast. Then, in term of mathematical equation, the equation for the preliminary mathematical model would follow the simple method equation which is given in the equation (1). Then, later it would be extended for Holt's Fit, Winter's Method and Holt-Winter Method.

3.2.5 Mathematical Model Development

Firstly, the exact load demand data would be plotted to figure out its graph outline. Then, by using the simple method, a forecast graph is plotted. This forecast graph would replicate the same graph outline of the exact load demand data. From this forecast graph, an exponential smoothing equation representing the exact load demand would be formulated. The formulation of the exponential smoothing equation is the objective of this final year project. Both graphs then would be plotted on the same plane to show its similarities and the replication. Then, after mathematical model of the simple method successfully be develop, the current model would be improved or extended by using Holt's Fit, Winter's Method and Holt-Winter Method.

3.2.6 Model Validation and Error Calculation

In this step, the mathematical model developed will be validated with the exact data to determine the percentage of error deviation. In this project, we use means absolute percentage error (MAPE) as our guidance for model performance. A lower MAPE would means a better model compares to a higher MAPE. The formulation to calculate MAPE is given in the equation (15) which is:

$$Absolute\ Error\ =\frac{|Forecast\ Load\ -\ Actual\ Load|}{Actual\ Load}\ \times\ 100\% \qquad (15)$$

Finally, the load demand model that has the lowest MAPE would be chosen as the best model. This model would be invaluable for a forecaster in making a good forecast of load demand and for GDC in their operation and planning.

3.3 Project Schedule and Milestone

In order to effectively conduct the project and complete it within the timeframe, the Gantt chart and Milestones for two semester duration has been conducted. The Gantt chart for final year project 1 is shown in Table 1 while the milestone for final year project 1 is shown in Table 2.

Table 1 Gantt Chart for Final Year Project I

ACTIVITIES	**FINAL YEAR PROJECT 1**													
	WEEK NO.													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
LITERATURE REVIEW AND BACKGROUND STUDY														
GDC LOAD DEMAND DATA GATHERING														
ANALYSE THE DATA														
PRELIMINARY MODELLING														
REPORT WRITING														

Table 2 Milestone for Final Year Project I

ACTIVITIES	**DUE DATE (WEEK)**
COMPLETION OF LITERATURE REVIEW	6
COMPLETION OF GDC LOAD DEMAND DATA GATHERING	8
COMPLETION OF ANALYSING THE DATA	11
PRELIMINARY MODELLING	14
DOCUMENTATION OF REPORT	14

For final year project 2, the Gantt chart is shown in Table 3 while the milestone for final year project 2 is shown in Table 4.

Table 3 Gantt Chart for Final Year Project II

ACTIVITIES	FINAL YEAR PROJECT 2													
	WEEK NO.													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
PRELIMINARY MODEL IMPROVEMENT														
FINAL MATHEMATICAL MODEL FORMULATION														
UTP LOAD DEMAND BEHAVIOUR ANALYSIS														
REPORT WRITING														

Table 4 Milestone for Final Year Project II

ACTIVITIES	DUE DATE (WEEK)
Completion of Preliminary Model Improvement	8
Completion of Mathematical Model Formulation	10
Completion Load Demand Behaviours Analysis	12
Documentation of report	14

3.4 Tools

The main software use in order to complete this project is Microsoft Excel 2010 since it is highly efficient in performing mathematical calculation and analysis. Besides, a Microsoft Excel plugin namely solver would be used to assist in calculating the variable estimation. This plugin must enable for that purpose.

3.5 Project Schedule

The schedule for Final Year Project I and II are depicted in Table 5 and Table 6.

Table 5 Project schedule for Final Year Project I

Component Submission	**Time (Week)**
Title Selection	Week 1
Extended Proposal	Week 6
Proposal Defence	Week 9
Draft Report	Week 13
Final Report	Week 14

Table 6 Project schedule for Final Year Project II

Component Submission	**Time (Week)**
Pre-EDX	Week 8
Draft Report	Week 13
Final Report	Week 14
VIVA	Week 15

CHAPTER 4
RESULT AND DISCUSSION

The load demand data for year 2011 was collected from the Gas District Cooling (GDC). Then, this load demand data is sorted in weekly basis to see the pattern of load demand for each day. Then, by referring to the 2011 calendar, the holiday is highlighted to differentiate between lecture days, holiday load demand and special event such as study week, examination week and trip.

For the information, this load demand data is the representations of maximum load that occur for each day in a year. Thus, from this load demand data, ones cannot differentiate between load demands at UTP before and after tripping occur since the load seems to be similar. Logically, the load demand from GDC would be dropped in tripping day however since the data is about the recorded maximum load, the load would just be similar. The examples of this happen on week 11 and week 27.

The load demand data of year 2011 for the actual load demand and forecast load demand has been plotted on the same X-Y plane in Microsoft Excel 2010. There are four types of exponential smoothing that have been investigated which are:-

1. Simple Exponential Smoothing
2. Exponential Smoothing with Trend (Holt's Fit)
3. Exponential Smoothing with Seasonality (Winter's method)
4. Holt-Winters Exponential Smoothing

A model that has the lowest MAPE would be chosen as the final model for representing the load demand of UTP.

4.1 The Simple Method

The simple method is based on equation (1). Firstly, value of the first estimation y_1 need to be determined. Based on [13] the initial value of y_1 is chosen to be equal to initial value of load demand X_1. Then, based on equation (1), a model of this equation is constructed on Microsoft Excel 2010. The value of alpha coefficient α for the first try is set as 0.35. The means absolute percentage error (MAPE) for this model is calculated then.

Next, to visually compare the performance of the exponential smoothing model, both graph of the exact load and the modelled load is plotted on the same X-Y plane as shown in Figure 2. The blue coloured plot is represent the actual load demand data of 2011 while the red coloured plot represents the load demand based on simple exponential equation.

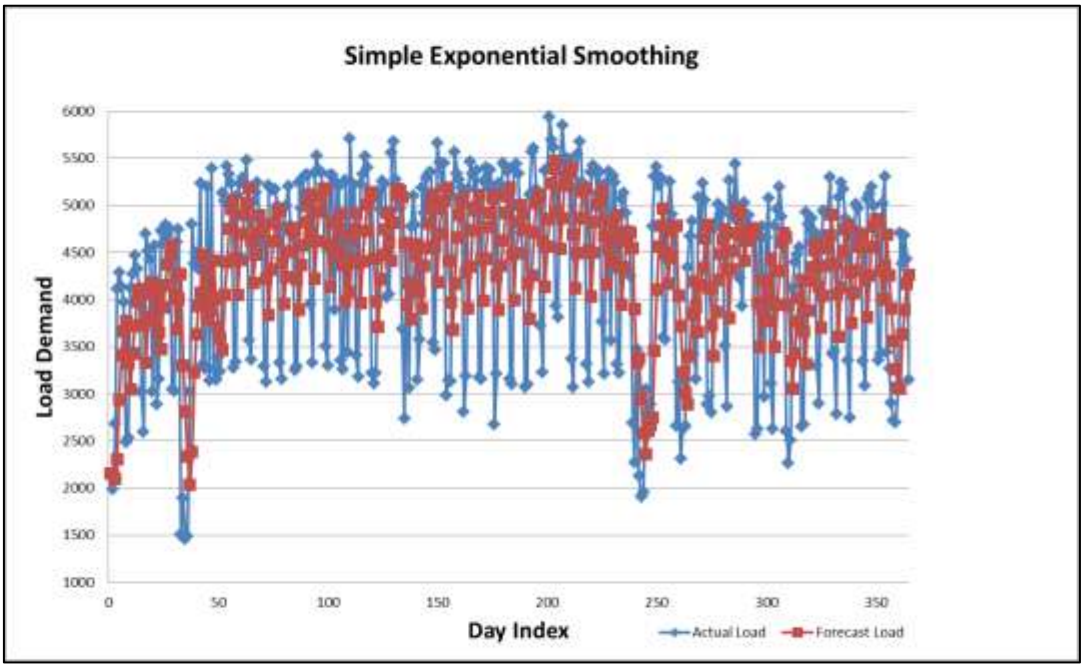

Figure 2 Simple Method Exponentially Smoothing Alpha = 0.35

From the above figure, it can be seen that the forecast load demand and the actual load demand have the same graph outline pattern but with a big gap. The MAPE recorded for this test is 26.51.

Then, the next test with value of alpha coefficient equal to 0.85 shows a big improvement in term of MAPE. The MAPE for 0.85 value of lambda is 23.05. This graph is shown in Figure 3.

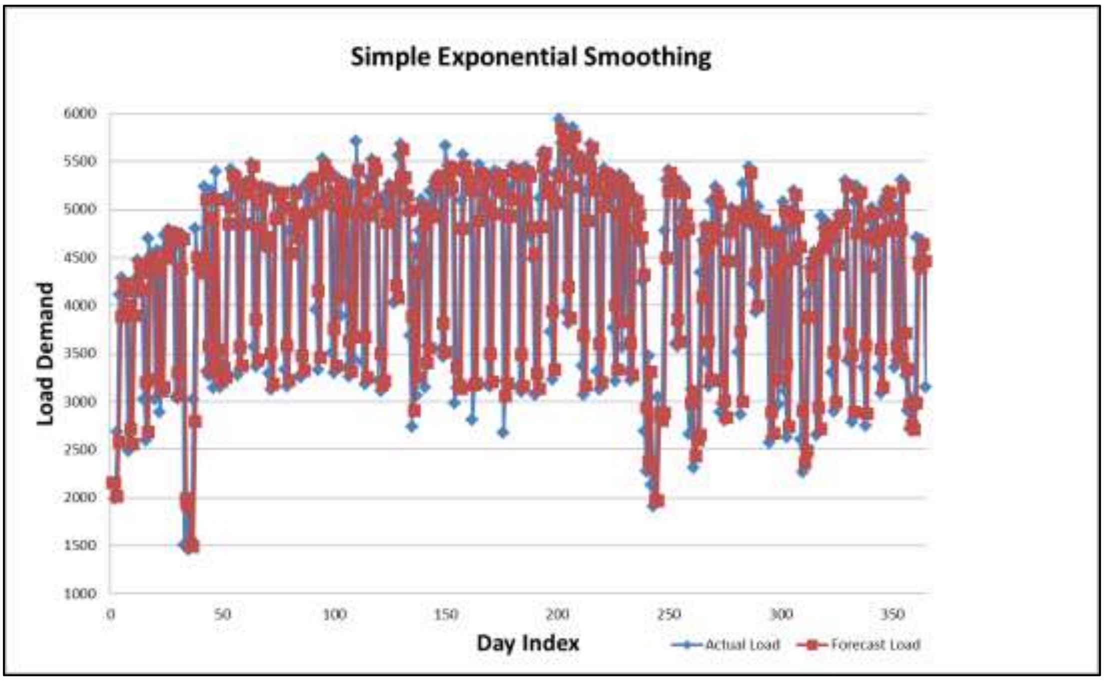

Figure 3 Simple Method Exponentially Smoothing Alpha Alpha = 0.85

For the determination of the best value of alpha coefficient for the first order exponential smoothing, the Microsoft Excel 2010 plugin namely solver parameter is used. The setting for this plugin is to calculate the value of alpha α that would result in the lowest MAPE. The procedures to use this plugin are as follows:

1. Open solver parameter plugin in excel data menu interface
2. For set objective, choose the MAPE cell in excel
3. For to, choose Min
4. For By Changing Variable Cells, choose alpha coefficient cell
5. Add constraint, alpha coefficient cell less than or equal to 1

The interface of this plugin is shown in Figure 4.

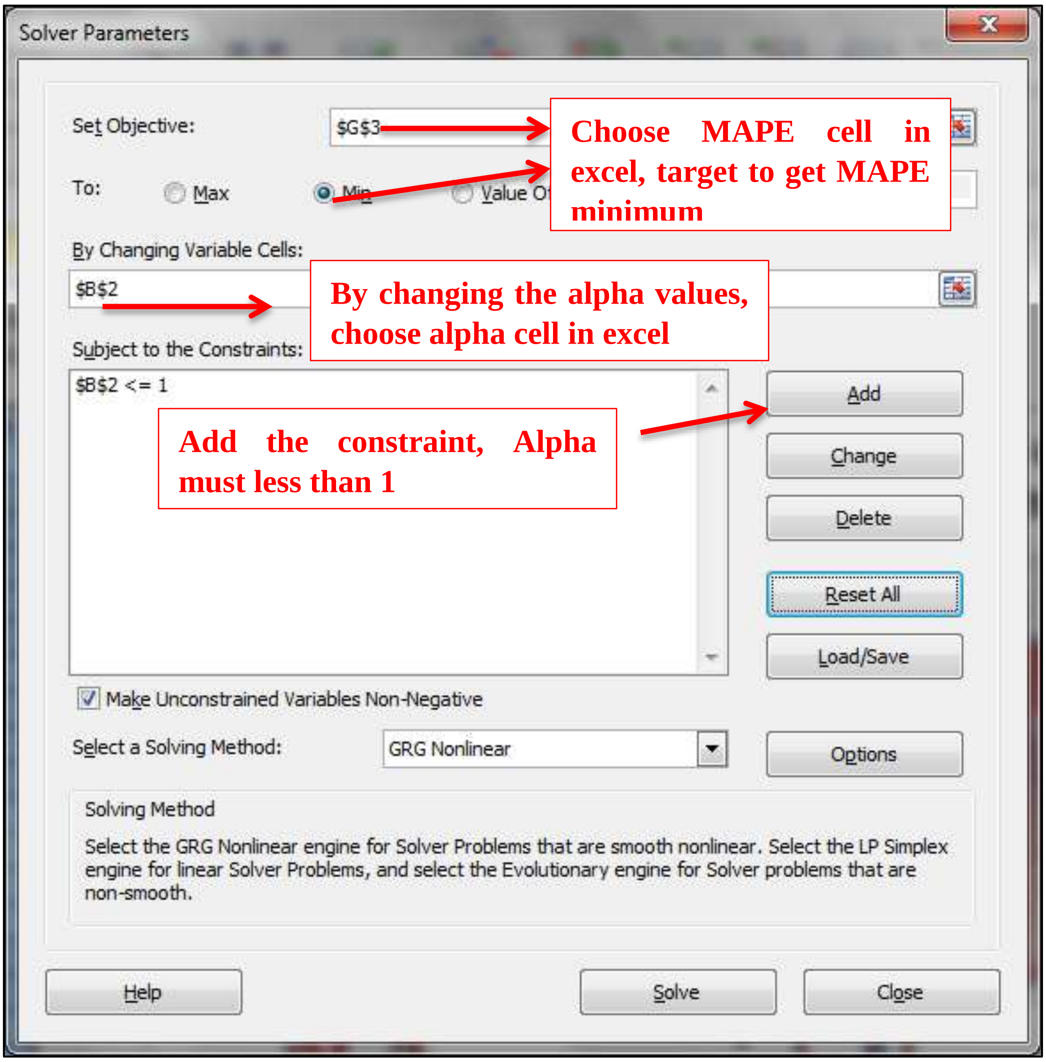

Figure 4 Solver Parameter Plugin

Then, the result for the best value of alpha that would give lowest MAPE based on this plugin is 0.9846527. This plugin has automatically done the iteration process for determination of the lowest MAPE that can be obtained in the first order exponential smoothing method. The MAPE for this case is 22.56 and the graph outline is shown in Figure 5.

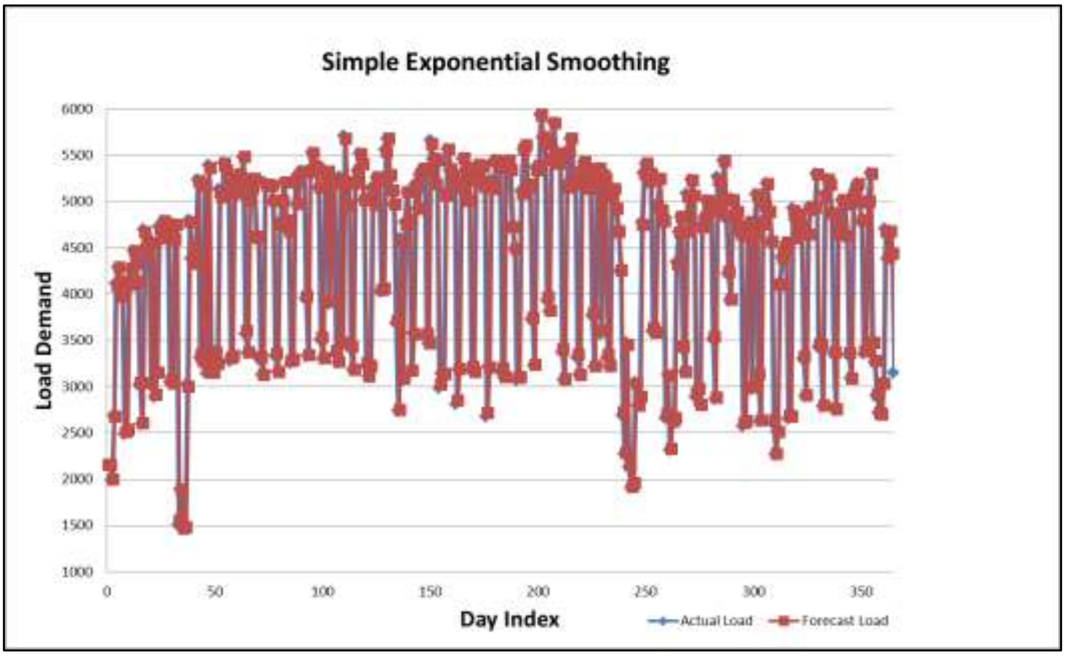

Figure 5 Simple Method Exponentially Smoothing Alpha 0.98465

From several tests that have been conducted, a table of coefficient α and the result of MAPE is constructed to see the effect of coefficient to the MAPE as shown in Table 7.

Table 7 Coefficient α vs MAPE

Coefficient, α	**MAPE (%)**
0.25	26.78
0.35	26.51
0.45	25.99
0.85	23.05
0.985	22.56
0.986	22.57
0.95	22.61

From Figure 5, it can be noticed that both actual load graph outline and forecast load graph outline have the identical graph pattern. Then, on Table 7 it is shown that, as alpha coefficient increases from 0.25 to 0.985 the MAPE is reduced. However, MAPE start to increase when the coefficient α, is above 0.985. So, this means that the best value for the coefficient, α is 0.985. Thus, the best equation for the simple method as in equation (16) is:

$$\boldsymbol{y_{t+1} = 0.985X_t + (0.015)y_t} \tag{16}$$

Where;

y_{t+1} is the next load demand

X_t is the previous load demand at moment t

y_t is the smoothed value of previous load demand at moment t

The means absolute percentage error (MAPE) of this model is **22.56**. Although the value of MAPE is high, this model would be improved later on by applying the next stages of exponential smoothing.

4.2 The Holt's Fit

The Holt's Fit is based on equation (2) and (3). In this method, the equation of y_{t+1} is modified by inserting the trend. The initial value of y_1 is chosen to be equal to initial value of load demand x_1. Meanwhile, the first value of trend is calculated by using equation (6). Then, by using solver plugin, the best value of α and β are determined. From the calculation obtain, the best value of α is equal to 0.9 and β is equal to 0.1. The MAPE obtained for this Holt's Fit exponential smoothing is 19.65% slightly better from the simple method which has MAPE of 22.56%.Figure 6 shows the screenshot of the performance of the Holt's Fit.

From several tests that have been conducted, a table of coefficient α, β and the result of MAPE is constructed to see the effect of coefficients to the MAPE as shown in Table 8.

Table 8 Coefficient α ,β vs MAPE

Coefficient, α	**Coefficient, β**	**MAPE (%)**
0.70	0.40	22.73
0.80	0.15	20.64
0.90	0.30	19.84
0.90	0.10	19.65
0.95	0.10	19.66

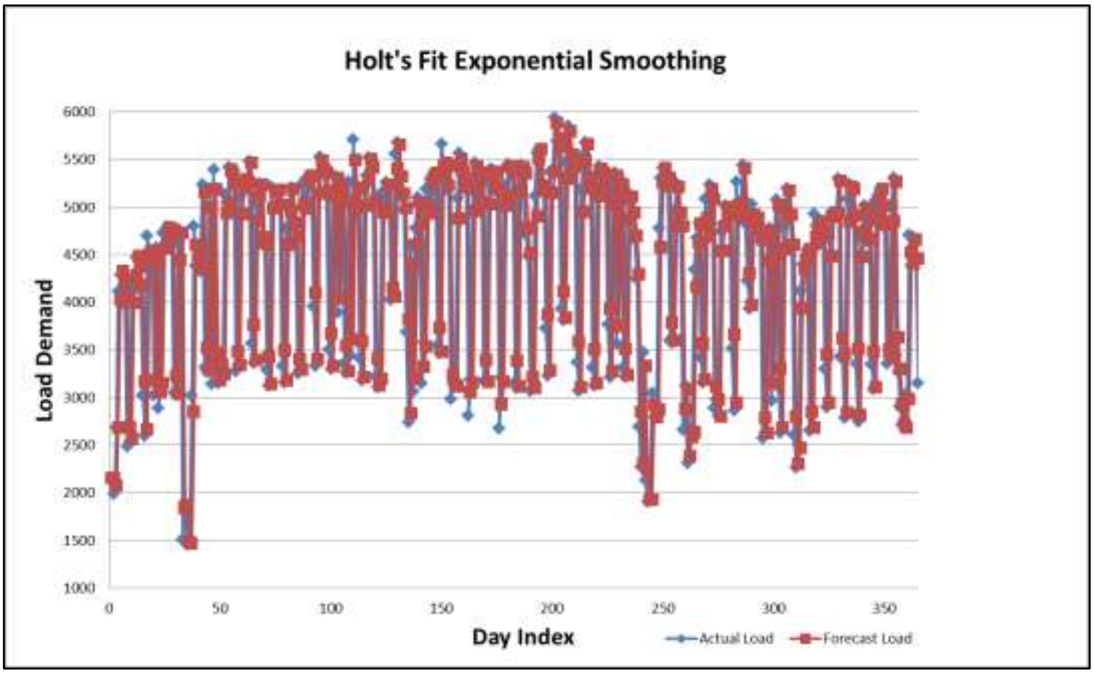

Figure 6 Holt's Fit Exponential Smoothing

The best equation for second order of exponential smoothing:

$$\boldsymbol{y_{t+1} = 0.99.x_t + (0.01).(y_{t-1} + T_{t-1})} \qquad 0 < \alpha < 1 \qquad (17)$$

$$\boldsymbol{T_{t+1} = 0.032(y_{t+1} - y_t) + (0.968).(T_t)} \qquad 0 < \beta < 1 \qquad (18)$$

4.3 Winters Method

The Winter's method is based on equations (7). For this type of exponential smoothing, the load demand data is grouped into their identical load pattern. For load demand of 2011, 7 clusters of load demand has been grouped and tabulated in Table 9:

Table 9 Seasonality

No	Seasonality, $\boldsymbol{S}$
1	Celebration, Sc
2	Weekend, Sw
3	Holiday, Sh
4	Jan Sem, Sj
5	May Sem, Sm
6	Sept Sem, Ss
7	Sem Break, Sb

The seasonality for each load is unique. The Celebration seasonality represents key celebrations in Malaysia which are Chinese New Year (CNY) and Eid-Fitri. Then, Holiday seasonality represents other celebration in Malaysia except CNY and Eid-Fitri. The examples are Thaipusam, Deepavali and Christmas. Weekend seasonality represents Saturday and Sunday excluded Saturday and Sunday in the festival, celebration and semester break period. Jan Sem, May Sem and Sept Sem represent the January semester, May semester and September semester weekdays. Finally, the Sem Break seasonality represents semester break based on UTP academic calendar and it is including the weekend.

Then for each cluster, we need to compute their weight of occurrences to the whole load demand of 2011. The total of seasonality should equal to the number of seasonality [15]. To compute this, once again we use excel plugin name solver to give the best probability for each cluster that would result in the lowest means absolute percentage error (MAPE). The equation for the Winter's method is given in equation:

$$\boldsymbol{y_{t+1} = [0.14X_t + (0.86)y_t]\text{x}\, S} \quad (19)$$

Where;

The weight for the seasonality is stated in Table 10.

Table 10 Winter Method Seasonality Weight

Seasonality, S	**Weight**
Celebration, Sc	0.57
Weekend, Sw	0.72
Holiday, Sh	0.75
Jan Sem, Sj	1.19
May Sem, Sm	1.16
Sept Sem, Ss	1.18
Sem Break, Sb	1.43
Total	7

The total seasonality is equal to 7 since there are 7 attributes. The example of seasonality factors calculation for Winter's Method is shown in equation 20. In this example, the weekend seasonality is chosen. Only the selected seasonality would have weightage value, other seasonality would have zero weightage.

$$y_{t+1} = [\mathbf{0.14}X_t + (\mathbf{0.86})y_t]\mathrm{x}\, S \tag{20}$$

Where;

$Sc = Sh = Sj = Sm = Ss = Sb = 0\ Sw = 0.72$

For this Winter's exponentially method, the MAPE obtained is 9.89.The graphical performance of Winter's Method is shown in Figure 7.

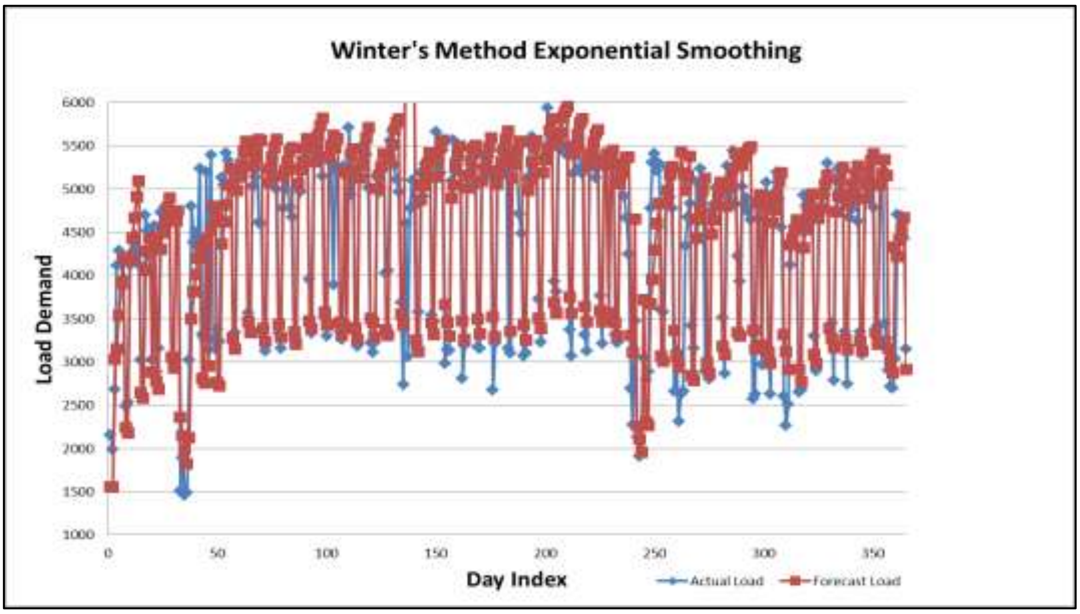

Figure 7 Winter's Method Exponential Smoothing

4.4 The Holt Winter Method

The Holt Winter method is based on equation (8) and (9).For this method, there are three estimates included in the equation which are smoothed value, trend and seasonality. The seasonality of Holt Winter method follow the same seasonality attributes of Winter's method in Table 9. However, the values or weightage for each attributes are not the same as calculated by solver plugin of Microsoft Excel. The weight of each attributes for Holt Winter method is shown in Table 11 while the equation for Holt Winter method is shown in equation 21.

$$\mathbf{y_{t+1}} = [\mathbf{0.31x_t} + \mathbf{0.69}(\mathbf{y_{t-1}} + \mathbf{T_{t-1}})]\mathbf{X}\, S \tag{21}$$

Where;

$\mathrm{T_{t+1}} = 0.21(\mathrm{y_{t+1}} - \mathrm{y_t}) + (0.79)\mathrm{T_t}$

Table 11 Holt Winter Seasonality Weight

Seasonality, S	**Weight**
Celebration, Sc	1.11
Weekend, Sw	0.70
Holiday, Sh	0.75
Jan Sem, Sj	1.17
May Sem, Sm	1.19
Sept Sem, Ss	1.20
Sem Break, Sb	0.89
Total	**7**

For this Holt Winter exponentially method, the MAPE obtained is 14.07%. The graphical performance of Holt Winter method is shown in Figure 8.

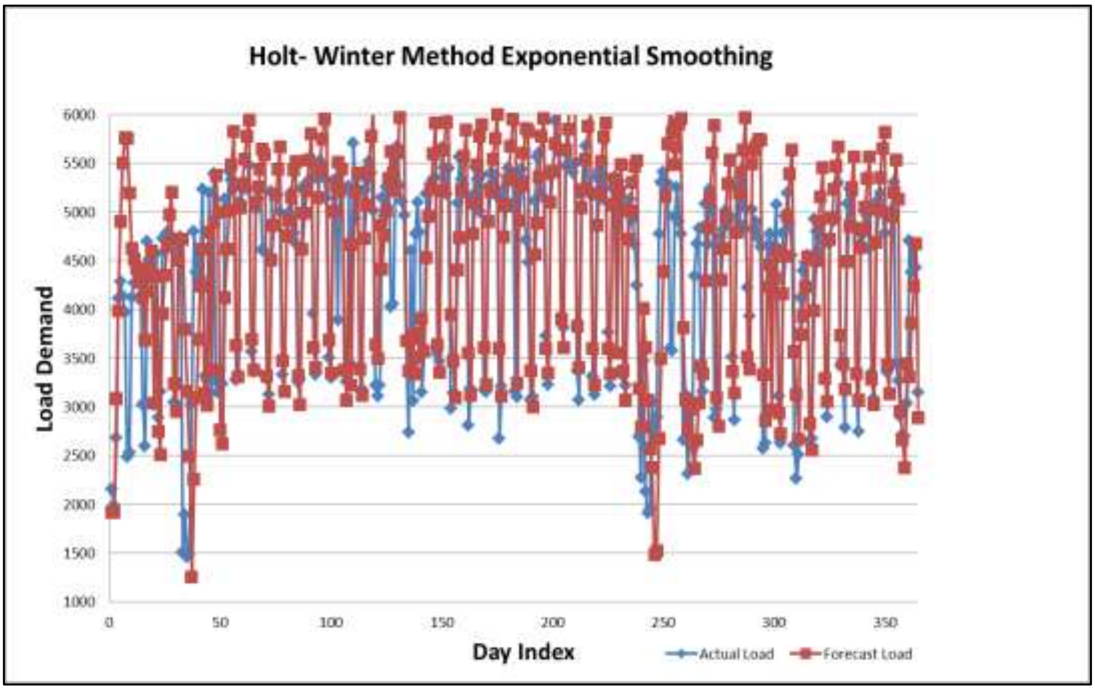

Figure 8 Holt Winter Exponential Smoothing

CHAPTER 5
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Mathematical model for load demand can be achieved by using various methods available. For this model, exponential smoothing is chosen since it is simple yet gives satisfactory result in term of graph outline and MAPE. A good and reliable mathematical model will produce better forecast result with lower percentage of means absolute percentage error (MAPE). However, as we use the times series technique, it cannot be compared to the result of the artificial intelligence such as artificial neural network and fuzzy logic.

In this paper, four types of exponential smoothing method have been tested which are Simple method, Holt's Fit, Winter's method and Holt Winter method. The performance of each model is summarized in Table 12. Based on the table, Winter's method obtain the lowest percentage of MAPE which is 9.89 followed by Holt-Winter, Holt's Fit and Simple method.

Table 12 Mathematical Model Performance

Mathematical Model	**MAPE %**
Simple Method	22.56
Holt's Fit	19.65
Winter's Method	9.89
Holt-Winter Method	14.07

Since Winter's method obtained the lowest percentage of MAPE, the method is selected as the best model to replicate the 2011 GDC load demand data. Ability of exponential smoothing method to achieve MAPE of value below 10% is satisfactory.

Lastly, it is hope that the mathematical model developed would be beneficial for Gas District Power (GDC) Plant in their forecast, operation and planning purposes. The objectives of this project which are to analyses and study the load demand behavior of UTP and then formulate the mathematical model has been successfully met.

5.2 Recommendation

As a pioneer project of developing mathematical model for Gas District Cooling (GDC) plant, it is recommended if the model can be tested for another period of case study. The suggestion is for period of four month which according to UTP tri-semester system. Since, a shorter period of forecasting would result in a more accurate result. Thus, it will be able to reduce the MAPE percentage lower that 9.89 that have been obtain in Winter's Method.

Besides, it is also recommended that other method is used to develop the mathematical model of GDC for the same period of case study. By doing so, the performance of Winter's method mathematical model can be compared. This comparative study can benefit the GDC plant in obtaining the best mathematical model for their purposes. For the researcher, such comparative study will enable them to know which method that has better performance.

APPENDIX A

INTRA-WEEK LOAD DEMAND DATA FOR 2011

COLOR	REPRESENTATION
	SEM OFF
	MID SEMESTER BREAK
	HOLIDAY
	TRIP
	STUDY WEEK
	EXAM WEEK
	WEEKEND
	WEEKDAY

DAY	MON	TUES	WED	THURS	FRI	SAT	SUN	INFO
WEEK 1						2152	1992	SEM OFF/TRIP
WEEK 2	2684	4112	4288	4136	3972	2488	2532	SEM OFF
WEEK 3	4124	4272	4468	4328	4128	3024	2596	SEM OFF
WEEK 4	4696	4520	4428	3020	4568	2888	3156	THAIPUSAM
WEEK 5	4728	4604	4792	4680	4756	3044	3028	
WEEK 6	4612	4748	1508	1892	1460	1488	3020	CNY/ TRIP
WEEK 7	4804	2204	4492	4328	5232	3320	3268	
WEEK 8	5196	3140	5396	3260	3152	3376	3240	MAULIDUR RASUL
WEEK 9	5132	5048	5416	5328	5232	3276	3336	
WEEK 10	5112	5224	5288	5244	5480	3568	3364	
WEEK 11	5032	5140	5244	4612	4600	3296	3124	MIDSEM BREAK/TRIP
WEEK 12	5212	5180	5164	5172	5000	3328	3156	
WEEK 13	4776	5000	5204	4784	4672	3256	3296	
WEEK 14	5244	4968	5296	5324	5322	3952	3332	
WEEK 15	5348	5524	5372	5352	5148	3504	3304	
WEEK 16	5320	5320	3892	5244	5196	3356	3264	
WEEK 17	5268	3444	5712	4936	5216	3408	3180	SULATN PERAK/ TRIP
WEEK 18	5228	5328	5516	5400	5012	3224	3112	STUDY WEEK/ LABOUR DAY
WEEK 19	3220	5152	4956	5260	5228	4028	4056	EXAM WEEK
WEEK 20	5560	5676	5276	5112	4968	3688	2736	EXAM WEEK/TRIP
WEEK 21	4604	3064	4776	5104	4796	3152	3576	SEM OFF/TRIP
WEEK 22	5188	4916	5292	5336	5352	3544	3464	SEM MAY/TRIP
WEEK 23	5660	5460	1624	5448	2988	3140	3132	AGONG

APPENDIX B

PART OF LOAD DEMAND DATA IN EXCEL

Day	Load	Smoothed	Forecast	Error	Relative Error	Absolute Error
1	2152	2152.00	2152.00	0.00	0.00	0.00
2	1992	2016.00	2152.00	-160.00	-8.03	8.03
3	2684	2583.80	2016.00	668.00	24.89	24.89
4	4112	3882.77	2583.80	1528.20	37.16	37.16
5	4288	4227.22	3882.77	405.23	9.45	9.45
6	4136	4149.68	4227.22	-91.22	-2.21	2.21
7	3972	3998.65	4149.68	-177.68	-4.47	4.47
8	2488	2714.60	3998.65	-1510.65	-60.72	60.72
9	2532	2559.39	2714.60	-182.60	-7.21	7.21
10	4124	3889.31	2559.39	1564.61	37.94	37.94
11	4272	4214.60	3889.31	382.69	8.96	8.96
12	4468	4429.99	4214.60	253.40	5.67	5.67
13	4328	4343.30	4429.99	-101.99	-2.36	2.36
14	4128	4160.29	4343.30	-215.30	-5.22	5.22
15	3024	3194.44	4160.29	-1136.29	-37.58	37.58
16	2596	2685.77	3194.44	-598.44	-23.05	23.05
17	4696	4394.46	2685.77	2010.23	42.81	42.81
18	4520	4501.17	4394.46	125.54	2.78	2.78
19	4428	4438.98	4501.17	-73.17	-1.65	1.65
20	3020	3232.85	4438.98	-1418.98	-46.99	46.99
21	4568	4367.73	3232.85	1335.15	29.23	29.23
22	2888	3109.96	4367.73	-1479.73	-51.24	51.24
23	3156	3149.09	3109.96	46.04	1.46	1.46
24	4728	4491.16	3149.09	1578.91	33.39	33.39
25	4604	4587.07	4491.16	112.84	2.45	2.45
26	4792	4761.26	4587.07	204.93	4.28	4.28
27	4680	4692.19	4761.26	-81.26	-1.74	1.74
28	4756	4746.43	4692.19	63.81	1.34	1.34
29	3044	3299.36	4746.43	-1702.43	-55.93	55.93
30	3028	3068.70	3299.36	-271.36	-8.96	8.96
31	4612	4380.51	3068.70	1543.30	33.46	33.46
32	4748	4692.88	4380.51	367.49	7.74	7.74
33	1508	1985.73	4692.88	-3184.88	-211.20	211.20
34	1892	1906.06	1985.73	-93.73	-4.95	4.95
35	1460	1526.91	1906.06	-446.06	-30.55	30.55
36	1488	1493.84	1526.91	-38.91	-2.61	2.61
37	3020	2791.08	1493.84	1526.16	50.54	50.54
38	4804	4502.06	2791.08	2012.92	41.90	41.90
39	2204	2548.71	4502.06	-2298.06	-104.27	104.27

APPENDIX C

UTP 2011 ACADEMIC CALENDAR

January 2011 Semester

PARTICULARS	NO. OF WEEKS	DATE	
		START	ENDS
Registration and Orientation of New Students	1	17 Jan 2011	23 Jan 2011
Registration of Existing Students	1 day	23 Jan 2011	
Lecture	7	24 Jan 2011	9 Mar 2011
Mid-Semester Break	4 days	10 Mar 2011	13 Mar 2011
Lecture	7	14 Mar 2011	29 Apr 2011
Study Week	5 days	30 Apr 2011	04 May 2011
Examination Week	11 days	05 May 2011	15 May 2011
End of Semester Break	1	16 May 2011	22 May 2011

May 2011 Semester

PARTICULARS	NO. OF WEEKS	DATE	
		START	ENDS
Registration and Orientation of New Students	4 days	19 May 2011	22 May 2011
Registration of Existing Students	1 day	22 May 2011	
Lecture	7	23 May 2011	6 Jul 2011
Mid-Semester Break	4 days	07 Jul 2011	10 Jul 2011
Lecture	7	11 Jul 2011	26 Aug 2011
Study Week	9 days	27 Aug 2011	04 Sep 2011
Examination Week	11 days	05 Sep 2011	15 Sep 2011
End of Semester Break	10 days	16 Sep 2011	25 Sep 2011

September 2011 Semester

PARTICULARS	NO. OF WEEKS	DATE	
		START	ENDS
Lecture	7	26 Sep 2011	09 Nov 2011
Mid-Semester Break	4 days	10 Nov 2011	13 Nov 2011
Lecture	7	14 Nov 2011	30 Dec 2011
Study Week	5 days	31 Dec 2011	04 Jan 2012
Examination Week	11 days	05 Jan 2012	15 Jan 2012
End of Semester Break	1	16 Jan 2012	22 Jan 2012

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