

COMBINED EMPIRICAL MODE DECOMPOSITION AND DYNAMIC  
REGRESSION MODEL FOR FORECASTING ELECTRICITY LOAD DEMAND

NURAMIRAH BINTI AKROM

A thesis submitted in fulfillment of the  
requirements for the award of the degree of  
Master of Science (Mathematics)

Faculty of Science  
Universiti Teknologi Malaysia

MARCH 2015

*To my beloved parents, siblings, and friends for their love, support, and  
encouragements.*

*I really appreciate it!*

## ACKNOWLEDGEMENT

First and foremost, I thank Allah (swt), the Lord Almighty, for giving me the health, the strength, and the ability to complete this thesis. Hamdallah. Then, I would like to express my deepest gratitude to my supervisor, Professor Zuhaimy Bin Ismail, who had given me a lot of guidance and helpful suggestions throughout this research. He encouraged, helped, and guided me in those times in need and I also would like to thank him for giving me the opportunity to acquire something new. In addition, my appreciation also goes to Dr Victor for contributing ideas and significant assistance.

Next, my deepest gratitude is also dedicated to my beloved family, especially my beloved parents, Mr Akrom Bin Noordin and Mdm Zaiton Binti Abdul Shakoor for their unconditional care, love, and moral support throughout my study in UTM. Their relentless support helped me a lot in completing this research. May Allah bless my parents.

Besides, I would like to thank the Malaysian Ministry of Higher Education for the financial support through My Master's Scholarship, and Universiti Teknologi Malaysia for their financial allowance through Zamalah Scholarship and not forgetting also to Tenaga Nasional Berhad (TNB) Malaysia for providing the electricity load demand data.

Lastly, I would like to extend my sincere appreciation to my friends, who kindly offered their suggestions, comments, and support. Their suggestions, comments, and support had been invaluable to me. Last but not least, I would like to thank all those who had directly and indirectly involved in completing this research.

## ABSTRACT

Electricity load demand forecasting is an important element in the electric power industry for energy system planning and operation. The forecast accuracy is the main characteristic in the forecasting process. Hence, in an attempt to achieve a good forecast, combined methods of empirical mode decomposition (EMD) and dynamic regression (DR), known as EMD-DR is proposed. Besides, the forecast performance of the combined model EMD and DR is compared with a single DR model. EMD is a powerful analysis technique for detecting non-stationary and nonlinear signal, while DR is a method that involves lagged external variables. The data used in this study are retrieved from half-hourly electricity demand (kW) and reactive power (var), whereby the reactive power data acts as exogenous variable for the DR method. The investigation is conducted using Statistical Analysis Software (SAS) for DR method and Matlab software for EMD. The findings reveal that the combined method, EMD-DR, give mean absolute percentage error (MAPE) 0.7237%, whereas for the DR method, 0.8074% is obtained, which suggests percentage improvement of 10.37%.

## ABSTRAK

Ramalan bebanan permintaan elektrik merupakan elemen yang penting dalam industri penjanaan kuasa elektrik; kerana kegunaannya dalam perancangan dan operasi jana kuasa elektrik. Ukuran kejituan merupakan karakter utama dalam proses ramalan. Untuk mendapatkan model yang terbaik, kajian ini telah mencadangkan kaedah penggabungan model penguraian mode empirikal (EMD) dan regresi dinamik (DR) yang dikenali sebagai model EMD-DR. Ukuran kejituan kaedah penggabungan EMD dan DR dibandingkan dengan model tunggal DR. EMD merupakan satu kaedah analisis yang mantap bagi mengesan amaran yang tidak tetap dan tidak linear, manakala kaedah DR merupakan kaedah yang melibatkan pembolehubah luaran tersusul. Data setiap setengah jam bebanan permintaan elektrik (kW) dan data kuasa bertindak balas (var) merupakan data yang digunakan dalam kajian ini, di mana data kuasa bertindak balas bertindak sebagai pembolehubah luaran untuk kaedah DR. Kajian dijalankan menggunakan perisian analisis statistikal (SAS) bagi kaedah DR dan perisian Matlab bagi EMD. Dapatan kajian menunjukkan ukuran peratus purata ralat mutlak (MAPE) bagi kaedah penggabungan, EMD-DR, adalah sebanyak 0.7237%, manakala kaedah DR sebanyak 0.8074% juga menunjukkan peningkatan kejituan sebanyak 10.37%.

## TABLE OF CONTENTS

| <b>CHAPTER</b> | <b>TITLE</b>                 | <b>PAGE</b>     |
|----------------|------------------------------|-----------------|
|                | <b>DECLARATION</b>           | <b>ii</b>       |
|                | <b>DEDICATION</b>            | <b>iii</b>      |
|                | <b>ACKNOWLEDGMENT</b>        | <b>iv</b>       |
|                | <b>ABSTRACT</b>              | <b>v</b>        |
|                | <b>ABSTRAK</b>               | <b>vi</b>       |
|                | <b>TABLE OF CONTENTS</b>     | <b>vii-xi</b>   |
|                | <b>LIST OF TABLES</b>        | <b>xii</b>      |
|                | <b>LIST OF FIGURES</b>       | <b>xiii-xv</b>  |
|                | <b>LIST OF ABBREVIATIONS</b> | <b>xvi-xvii</b> |
|                | <b>LIST OF APPENDICES</b>    |                 |
| <b>1</b>       | <b>INTRODUCTION</b>          | <b>1</b>        |
|                | 1.1 Introduction             | 1-2             |
|                | 1.2 Background of the Study  | 3               |
|                | 1.3 Problem Statement        | 3-4             |

|          |  |           |
|----------|--|-----------|
| 1.4      | Objectives of the Study  | 4         |
| 1.5      | Scope of the Study   | 5         |
| 1.6      | Significance of the Study                                      | 5-6       |
| 1.7      | Thesis Organization  | 6-7       |
| <b>2</b> | <b>LITERATURE REVIEW</b>                                       | <b>8</b>  |
| 2.1      | Introduction   | 8         |
| 2.2      | Load Forecasting   | 8-9       |
| 2.2.1    | Short Term Load Forecast (STLF)                                | 9         |
| 2.3      | Overview of Energy   | 10        |
| 2.3.1    | Electricity Load Demand  | 10        |
| 2.3.2    | Reactive Power   | 10-14     |
| 2.4      | A Review on Dynamic Regression (DR)                            | 14-16     |
| 2.4.1    | Strengths and Weaknesses of Dynamic Regression (DR)            | 16-18     |
| 2.5      | A Review on Empirical Mode Decomposition (EMD)                 | 18        |
| 2.5.1    | Strengths and Weaknesses of Empirical Mode Decomposition (EMD) | 18-20     |
| 2.6      | Related Researches on Dynamic Regression (DR)                  | 20-22     |
| 2.7      | Related Researches on Empirical Mode Decomposition (EMD)       | 23-26     |
| 2.8      | Conclusions  | 27        |
| <b>3</b> | <b>RESEARCH METHODOLOGY</b>                                    | <b>28</b> |
| 3.1      | Introduction   | 28        |
| 3.2      | Dynamic Regression (DR) Methodology                            | 28-32     |

|        |   |       |
|--------|---|-------|
| 3.2.1  | Correlation   | 32-34 |
|        | 3.2.1.1 Simple Linear Regression  | 35    |
|        | 3.2.1.2 The Coefficient of Determination                                      | 35    |
|        | 3.2.1.3 Standard Error  | 36    |
|        | 3.2.1.4 Scatter Plot  | 36    |
| 3.2.2  | Single-Input Transfer Function Models   | 36-37 |
| 3.2.3  | Box-Jenkins ARIMA Model   | 37    |
| 3.2.4  | Box-Jenkins Seasonal ARIMA Model  | 38    |
| 3.2.5  | Autocorrelation Function (ACF) and Partial<br>Autocorrelation Function (PACF) | 39    |
|        | 3.2.5.1 Autocorrelation Function (ACF)  | 39    |
|        | 3.2.5.2 Partial Autocorrelation Function<br>(PACF)                            | 40-42 |
| 3.2.6  | Box-Jenkins Double Seasonal ARIMA Model                                       | 42    |
| 3.2.7  | Dynamic Regression (DR) Model   | 43    |
| 3.2.8  | Cross Correlation Function  | 43-44 |
|        | 3.2.8.1 Sample Cross Correlations   | 44-45 |
|        | 3.2.8.2 Pre-whitening   | 45-47 |
| 3.2.9  | Parameter Estimation  | 47-48 |
| 3.2.10 | Steps of Building Dynamic Regression (DR)                                     | 48-50 |
|        | 3.2.10.1 Theoretical Framework of Dynamic<br>Regression (DR) Model            | 51    |
| 3.3    | Empirical Mode Decomposition (EMD)  | 52    |
|        | 3.3.1 Description of the EMD  | 52-53 |
|        | 3.3.2 Envelopes   | 53-54 |
|        | 3.3.3 Intrinsic Mode Function   | 54-55 |



|          |   |           |
|----------|---|-----------|
| 3.3.4    | Steps of Building Sifting Algorithm                                     | 55-56     |
| 3.3.4.1  | Theoretical Framework of Sifting Algorithm                              | 57        |
| 3.4      | Empirical Mode Decomposition and Dynamic Regression (EMD-DR) Model      | 58        |
| 3.4.1    | Interpolation   | 58-59     |
| 3.4.2    | Theoretical Framework of EMD-DR Model                                   | 60        |
| 3.5      | Model Selection Criteria  | 61        |
| 3.6      | Mean Absolute Percentage Error  | 62        |
| 3.7      | Concluding Remarks  | 62        |
| <b>4</b> | <b>DYNAMIC REGRESSION MODEL FOR FORECASTING ELECTRICITY LOAD DEMAND</b> | <b>63</b> |
| 4.1      | Introduction  | 63        |
| 4.2      | The Data Series   | 64-65     |
| 4.3      | Correlation Analysis  | 66        |
| 4.4      | Regression Analysis   | 67-68     |
| 4.5      | Results   | 68-69     |
| 4.5.1    | Pre-processing Data   | 69-72     |
| 4.5.2    | Model Identification  | 72        |
| 4.5.2.1  | Transfer Function Model   | 73-74     |
| 4.5.3    | Model Estimation  | 75-76     |
| 4.5.4    | Model Checking  | 76-78     |
| 4.5.5    | Forecasting Process   | 79-81     |
| 4.6      | Conclusion  | 81        |

|          |  |                |
|----------|--|----------------|
| <b>5</b> | <b>EMPIRICAL MODE DECOMPOSITION AND DYNAMIC REGRESSION MODEL FOR FORECASTING ELECTRICITY LOAD DEMAND</b> | <b>82</b>      |
| 5.1      | Introduction   | 82             |
| 5.2      | The Basics of Empirical Mode Decomposition (EMD)   | 83             |
| 5.2.1    | The IMFs for Electricity Load Demand and Reactive Power data   | 83-96          |
| 5.3      | EMD-DR Implementation  | 96-98          |
| 5.4      | Load Forecasting using EMD-DR model  | 98-101         |
| 5.5      | Comparison between EMD-DR and Dynamic Regression (DR) Model  | 102-104        |
| 5.6      | Summary  | 105            |
| <b>6</b> | <b>CONCLUSIONS AND RECOMMENDATIONS</b>   | <b>106</b>     |
| 6.1      | Introduction   | 106            |
| 6.2      | Results and Discussions  | 106-107        |
| 6.3      | Conclusions  | 107            |
| 6.4      | Recommendations  | 108            |
|          | <b>BIBLIOGRAPHY</b>  | <b>109-118</b> |
|          | <b>Appendices A-C</b>  | <b>119-128</b> |

## LIST OF TABLES

| TABLE NO. | TITLE  | PAGE  |
|-----------|--|-------|
| 2.1       | A summary of some load forecasting studies using the Dynamic Regression (DR) approach            | 25    |
| 2.2       | A summary of some load forecasting studies using the Empirical Mode Decomposition (EMD) approach | 26    |
| 3.1       | The ACF and PACF characteristics for a process that is considered stationary.                    | 41    |
| 3.2       | The guidelines of choosing seasonal operators  | 41-42 |
| 4.1       | The parameter estimation for Double Seasonal ARIMA and Transfer Function model.                  | 75-76 |
| 4.2       | The AIC and SBC of the selected model  | 77    |
| 4.3       | The MAPE of in-sample and out-sample forecasts of DR model                                       | 79    |
| 5.1       | The correlation coefficient, Standard errors, AIC and SBC of IMFs.                               | 97    |
| 5.2       | Electricity load demand predictive equations using EMD-DR model.                                 | 98-99 |
| 5.3       | The MAPE of in-sample and out-sample forecasts of EMD-DR model                                   | 100   |
| 5.4       | Comparison of forecasting performance using EMD-DR and DR models.                                | 102   |

## LIST OF FIGURES

| FIGURE NO. | TITLE  | PAGE |
|------------|--|------|
| 2.1        | The phase of apparent power $S$ , reactive power $Q$ , and the real power, $P$ .   | 11   |
| 2.2        | A thyristor to produce reactive power  | 13   |
| 3.1        | Flow chart of theoretical framework of DR model  | 51   |
| 3.2        | Flow chart of theoretical framework of sifting algorithm.  | 57   |
| 3.3        | Flow chart of theoretical framework of EMD-DR Model.   | 60   |
| 4.1        | The time series plot of electricity demand and reactive power from January 1 <sup>st</sup> , 2013 to May 31 <sup>st</sup> , 2013 | 65   |
| 4.2        | The scatterplot of electricity demand (kW) versus reactive power (kvar) with sample regression line.                             | 67   |
| 4.3        | The ACF for electricity demand and reactive power  | 70   |
| 4.4        | The PACF for electricity demand and reactive power   | 70   |
| 4.5        | The ACF of electricity demand, $Y(t)$ , and reactive power, $X(t)$ , after $d = 1, D_1 = 1$ and $s_1 = 48$                       | 70   |
| 4.6        | The PACF of electricity demand, $Y(t)$ , and reactive power, $X(t)$ , after $d = 1, D_1 = 1$ and $s_1 = 48$                      | 71   |
| 4.7        | Electricity demand, $Y(t)$ , and reactive power, $X(t)$ , after $d = 1, D_1 = 1, s_1 = 48, D_2 = 1$ and $s_2 = 336$              | 71   |
| 4.8        | The ACF of electricity demand, $Y(t)$ , and reactive power, $X(t)$ after $d = 1, D_1 = 1, s_1 = 48, D_2 = 1$ and $s_2 = 336$     | 71   |

|      |   |    |
|------|---|----|
| 4.9  | The PACF of electricity demand, $Y(t)$ , and reactive power, $X(t)$ , after $d = 1, D_1 = 1, s_1 = 48, D_2 = 1$ and $s_2 = 336$ | 72 |
| 4.10 | The CCF of electricity demand, $Y(t)$ , and reactive power, $X(t)$ .  | 73 |
| 4.11 | The white noise problem in the selected model.  | 78 |
| 4.12 | The residual normality diagnostic of the selected model.  | 78 |
| 4.13 | Time series plot of electricity load demand and in-sample forecast for February, 2013.  | 80 |
| 4.14 | Time series plot of electricity load demand and out-sample forecast for May, 2013   | 81 |
| 5.1  | IMF 1 and IMF 2 of electricity load demand, $Y(t)$ , and reactive power, $X(t)$ .   | 85 |
| 5.2  | IMF 3 and IMF 4 of electricity load demand, $Y(t)$ , and reactive power, $X(t)$ .   | 86 |
| 5.3  | IMF 5 and IMF 6 of electricity load demand, $Y(t)$ , and reactive power, $X(t)$ .   | 87 |
| 5.4  | IMF 7 and IMF 8 of electricity load demand, $Y(t)$ , and reactive power, $X(t)$ .   | 88 |
| 5.5  | IMF 9 and IMF 10 of electricity load demand, $Y(t)$ , and reactive power, $X(t)$ .  | 89 |
| 5.6  | IMF 11 and IMF 12 of electricity load demand, $Y(t)$ and reactive power, $X(t)$ .   | 90 |
| 5.7  | IMF 13 and IMF 14 of electricity load demand, $Y(t)$ , and reactive power, $X(t)$   | 91 |
| 5.8  | IMF 15 and IMF 16 of electricity load demand, $Y(t)$ , and reactive power, $X(t)$ .   | 92 |
| 5.9  | IMF 17, IMF 18, and IMF 19 of reactive power, $X(t)$ .  | 93 |
| 5.10 | The residue (IMF 17) of electricity load demand, $Y(t)$ .   | 94 |
| 5.11 | The residue (IMF 20) of reactive power, $X(t)$  | 94 |

|      |   |     |
|------|---|-----|
| 5.12 | The new IMF16 of reactive power, $X(t)$ , after interpolation process.                | 95  |
| 5.13 | The new IMF 17 (residue) of reactive power after interpolation process.               | 96  |
| 5.14 | Time series plot of electricity load demand and in-sample forecast for EMD-DR model.  | 101 |
| 5.15 | Time series plot of electricity load demand and out-sample forecast for EMD-DR model. | 101 |
| 5.16 | In-sample forecasts of electricity load demand using DR and EMD-DR model.             | 103 |
| 5.17 | Out-sample forecasts of electricity load demand using DR and EMD-DR model.            | 104 |

## LIST OF ABBREVIATIONS

|           |   |   |
|-----------|---|---|
| TNB       | - | Tenaga Nasional Berhad  |
| PJM       | - | Pennsylvania-New Jersey-Maryland Interconnection                          |
| SAS       | - | Statistical Analysis Software   |
| STLF      | - | Short Term Load Forecast  |
| EMD       | - | Empirical Mode Decomposition  |
| DR        | - | Dynamic Regression  |
| EMD-DR    | - | Empirical Mode Decomposition and Dynamic Regression                       |
| IMFs      | - | Intrinsic Mode Functions  |
| W         | - | Watt  |
| kW        | - | Kilowatt  |
| kWh       | - | Kilowatt-hour   |
| VA        | - | Volt Ampere   |
| var       | - | Volt-amperes Reactive   |
| AC        | - | Alternating Current   |
| RMS       | - | Root Mean Square  |
| OLS       | - | Ordinary Least Square   |
| AR        | - | Autoregressive  |
| SAR       | - | Seasonal Autoregressive   |
| MA        | - | Moving Average  |
| SMA       | - | Seasonal Moving Average   |
| ARIMA     | - | Autoregressive Integrated Moving Average                                  |
| ARIMAX    | - | Autoregressive Integrated Moving Average with Exogenous Variable          |
| SARMAX    | - | Seasonal Autoregressive Moving Average with Exogenous Variable            |
| SARIMAX   | - | Seasonal Autoregressive Integrated Moving Average with Exogenous Variable |
| ANN       | - | Artificial Neural Network   |
| FFNN      | - | Feed Forward Neural Network   |
| MFNN      | - | Multi-output Feed Forward Neural Network                                  |
| BPNN      | - | Back Propagation Neural Network   |
| ARIMA-ANN | - | Autoregressive Integrated Moving Average and Artificial Neural Network    |
| GA        | - | Genetic Algorithm   |
| PSO       | - | Particle Swarm Optimization   |
| PSO-BP    | - | Particle Swarm Optimization and Back Propagation Neural Network           |
| PSO-SVR   | - | Particle Swarm Optimization and Support Vector Regression                 |
| GA-ARIMA  | - | Genetic Algorithm and Artificial Neural Network                           |

|                  |   |   |
|------------------|---|---|
| SVR              | - | Support Vector Regression   |
| LSSVM            | - | Least Square Support Vector Machine   |
| LSSVM-<br>ARIMAX | - | Least Square Support Vector Machine and Autoregressive<br>Integrated Moving Average with Exogenous Variable |
| EMDSVRAR         | - | Support Vector Regression hybridized with EMD method and<br>Auto Regression                                 |
| SES              | - | Seasonal Exponential Smoothing  |
| AFCM             | - | Adaptive Fuzzy Combination Model  |
| MCP              | - | Market Clearing Price   |
| MFES             | - | Multi-output Feed Forward Neural Network with EMD based<br>Signal Filtering and Seasonal Adjustment method  |
| MFE              | - | Multi-output Feed Forward Neural Network with EMD-based<br>Signal Filtering                                 |
| MFS              | - | Multi-output Feed Forward Neural Network with Seasonal<br>Adjustment  |
| AIC              | - | Akaike Information Criteria   |
| BIC              | - | Bayesian Information Criteria   |
| SSE              | - | Sum Square Error  |
| MAE              | - | Mean Absolute Error   |
| MSE              | - | Mean Square Error   |
| MAPE             | - | Mean Average Percentage Error   |



**LIST OF APPENDICES**

| <b>APPENDIX</b> | <b>TITLE</b>   | <b>PAGE</b> |
|-----------------|--|-------------|
| A               | SAS Coding for Dynamic Regression Model                      | 119         |
| B               | SAS Output for Dynamic Regression Model                      | 120-126     |
| C               | Mathlab Coding for Empirical Mode Decomposition<br>Technique | 127-128     |

## **CHAPTER 1**

### **INTRODUCTION**

#### **1.1 Introduction**

Forecasting is a vital activity in commerce, economics, energy industries, and marketing (Chatfield, 2004). The quality of forecast and its significance is an essential process because its implementation in managerial decision that is extended in numerous fields is needed. Throughout the years, diverse methods have been developed for forecast.

Chatfield (2004) categorized forecasting methods into three types, which are judgmental forecasts, univariate methods, and multivariate methods. Basically,

judgmental forecasts are related to instinctive perception, common sense, ‘inside’ and commercial comprehension. Meanwhile, univariate methods can be categorized as forecasts based only on past and present values of single series forecasting, very likely added by a function of time, for example, linear trend. On the other hand, multivariate method is a method of forecast of a specified variable that depends, leastwise partially, on values of one or extra time series variables, known as explanatory or predictor variables. Multivariate forecasts, mostly taking into account on a multivariate model, require more than one equation if the variables are jointly dependent.

Besides, combined methods can also be categorized as a forecasting method. This method could be merged with one of the above methods proposed by Chatfield (2004). For example, when univariate or multivariate forecasts are modified intuitively, which is also considered as exterior information that fails to show conventional aspect in a mathematical model, these combined methods are the most appropriate solution.

In this study, combined methods of univariate and multivariate had been introduced. The implementation of the combined methods is to improve the accuracy of forecast. Thus, in order to examine the effectiveness of the combined methods, a comparison study is conducted between single method and combined methods. Therefore, the following subsection describes the background of the study.

This chapter presents the background of the study. Next, it describes the problem statement, the objectives, the scope, and the significance of the study. Finally, a brief explanation for each chapter is provided at the end of this chapter.

## **1.2 Background of the Study**

This study attempted to forecast electricity load demand. The univariate method, such as Box-Jenkins (BJ) method, is one of the most famous methods for forecasting electricity load demand, while for multivariate method; most studies used regression analysis. Meanwhile, for load forecasting, combined methods is also one of the effective methods, such as ARIMA-ANN method, GA-ARIMA method, LSSVM-ARIMA method, and Gray method with ANN.

The purpose of this study is to forecast electricity load demand using combined methods of Empirical Mode Decomposition (EMD) and Dynamic Regression (DR). A single method of DR acted as a benchmark for the combined methods. The multivariate method, such as Dynamic Regression, has been frequently used for various similar studies because this method can include explanatory variables. On the other hand, EMD is a new method for load forecasting, and previous studies have proven the efficiency of forecasting performances using the EMD method.

In addition, this study highlighted the procedures on modeling and forecasting electricity load demand using the DR method and the combined methods of EMD and DR, thus a comparative study between these two methods is carried out.

## **1.3 Problem Statement**

The main issue in forecasting is the accuracy of forecast. Lately, a combination of two methods is believed to improve the forecasting performance compared to a single method. To produce accurate forecasts using DR model, the lagged external variables, which match the electricity demand series, must be identified first. Moreover,

forecasting electricity load demand is usually affected by other causal factors of data or disturbances, such as high frequency, non-stationary, non-constant variance and mean, and multiple seasonality, which are very likely related to half-hourly, hourly, daily, and weekly periodicity, and the calendar effects, for example, holidays and weekends. Therefore, modeling such data type poses multitude of challenges and the method must satisfy the causal factor that affects forecasting process. One of the methods that eliminate the causal factor of electricity demand data is the EMD method. Then, it had been necessary to combine the EMD with the DR method, in order to improve forecast accuracy, rather than using a single method and also to investigate the elimination of causal factor in electricity demand data.

#### **1.4 Objectives of the Study**

The purpose of this study is to develop the best model to forecast the Malaysian electricity load demand. In an attempt to discover the best model, some specific objectives had been needed. The objectives of the study are to:

- i) Model the electricity load demand data using DR and EMD methods.
- ii) Forecast electricity load demand using DR model, and a combined model of Empirical Mode Decomposition with Dynamic Regression (EMD-DR) model.
- iii) Conduct a comparative evaluation on the performance between DR and EMD-DR model.

## **1.5 Scope of the Study**

The scope of the study is divided into two, which are sample data series and method of forecasting. The data used in this study are half-hourly of electricity demand and reactive power from January 1<sup>st</sup> 2013 to May 31<sup>st</sup> 2013. The total data points are 14496 for both electricity demand and reactive power, and the units of measurements are Kilowatts (kW) and Volt-amperes Reactive (var) respectively.

Nevertheless, this study is limited to modeling and to forecasting electricity load demand by using DR method and a combined method of EMD-DR. The reactive power data acted as explanatory variables in the DR method. Lastly, a comparative study that looked into forecasting performance is conducted between a single model (DR) and a combined model (EMD-DR).

## **1.6 Significance of the Study**

The results from this study are useful to forecast electricity demand. The load forecasting results can be used in electricity generation, such as energy reservation and maintenance scheduling. Limitation of energy resources requires the employment of electric energy appropriately, more efficient power plants, and transmission lines. Thus, it is very important to forecast electricity demand correctly and accurately.

Besides, in the attempt to reveal the best model for forecasting electricity load demand, contributions have been made. The contribution is by investigating electricity load demand forecasting to assist in the expansion of new models that can lead to a

decrease in the forecast error of the already existing models, which will result to a rise in profit margin for energy industries.

Lastly, the results of this study help in contributing new literature pertaining to electricity load demand forecasting and the methodologies used. Furthermore, it may serve a guideline for those who would want to conduct a similar study.

## **1.7 Thesis Organization**

This thesis consists of six chapters. The first chapter is the introduction. This chapter provides the introduction, the background of the study, the problem statement, the objectives of the study, the scope, and the significance of the study.

Meanwhile, the Literature Review is in Chapter Two. This chapter represents the literature review on basic definition of load forecasting, short-term load forecast, and reactive power. Moreover, some strengths and weaknesses of DR and EMD methods are reviewed, and besides, some related researches on DR and EMD are presented. The conclusion and the summary are given to close the discussion of the chapter.

Next, Chapter Three is the Research Methodology. This chapter starts with a detailed discussion on DR and EMD methodologies, and then, it discusses the technique of combining EMD and DR procedures for load forecasting. The chapter ends with forecasting evaluation method and concluding remarks.

On the other hand, Chapter Four depicts the application of DR method to half hourly load demand in Malaysia. It begins with the introduction and a brief discussion on data series. Next, it discusses on analyzing the data using regression and correlation analyses. Then, it presents the procedures in determining Transfer Function model in detail. Finally, the discussions of the chapter are closed with the results of one-step ahead in-sample and out-sample forecast, and a conclusion of DR model.

After that, Chapter Five discusses the application of EMD-DR method in electricity load demand forecasting. First, it presents the introduction to the chapter, followed by the basic concepts of EMD, and the extraction of IMFs for electricity load demand and reactive power. Next, it presents EMD-DR implementation and the results of load forecasting using EMD-DR method. Lastly, a comparative study between the single and the combined models is discussed in this chapter and it ends with a summary.

Finally, Chapter Six ends the thesis by drawing up conclusions based on the results and findings, and also recommendations for future research.



**BIBLIOGRAPHY**

An, N. *et al.* (2013). *Using Multi-output Feed Forward Neural Network with Empirical Mode Decomposition Based Signal Filtering for Electricity Demand Forecasting*. Energy. Vol.49, pp.279-288.

Asean Energy Manager Accreditation Scheme (AEMES). (2010). AEMES Training Workbook. In *Module Code TC-5: Fundamental of Electrical System*. (pp. 30). Malaysia: AEMES.

Bai, W. *et al.* (2009). *Research of the Load Forecasting Model based on HHT and Combination of HHT*. In: 2009 Power and Energy Engineering Conference (APPEEC). pp. 1-4.\

Bhuiyan, S. M. A. *et al.* (2012). *Spatial Domain Sharpening of Color Image Employing Bidimensional Empirical Mode Decomposition*. Proc.Of SPIE. Vol. 8398, pp, 83980J-1 – 83980J-8.

Bowerman, B. L. and O'Connell, R.T. (1993). *Forecasting and Time Series. An Applied Approach. Third Edition*. California: Duxbury Press.

Bowerman, L. *et al.* (2005). *Forecasting, Time Series and Regression. An Applied Approach, Fourth Edition*. USA: Thomson Brroks/Cole.

Box, G. E. P. *et al.* (1994). *Time Series Analysis. Forecasting and Control*. New Jersey: Prentice Hall.

Box, G. E. P. *et al.* (2008). *Time Series Analysis. Forecasting and Control. Fourth Edition*. New Jersey: John Wiley & Sons

Box, G. E. P. and Jenkins. G. M. (1976). *Time Series Analysis. Forecasting and Control*. New Jersey: Holden-Day.

Brocklebank, J. C. and Dickey, D. A. (2003). *SAS for Forecasting Time Series, Second Edition*. USA: SAS Institute Inc.

Brockwell, P. J. and Davis, R. A. (1996). *Introduction to Time Series and Forecasting*. New York: Springer.

Cao, D. *et al.* (2010). *Gearbox Fault Diagnosis based on EEMD and Hilbert Transform*. Journal of Mechanical Transmission. Vol. 34(05), pp. 62-70.

Chatfield, C. (2004). *The Analysis of Time Series: An Introduction. Sixth Edition*. New York: Chapman & Hall.

Crayer, J. D and Chan, K. S. (2008). *Time Series Analysis with Applications in R, Second Edition*. New York: Springer Science + Business Media, LLC.

Crayer, J. D. and Chan, K. (2008). *Time Series Analysis with Application in R. Second Edition*. New York: Springer.

Cruz, A. et al. (2011). *The Effect of Wind Generation and Weekday on Spanish Electricity Spot Price*. Electric Power Systems Research, Vol. 81, pp.1924-1935.

Czarnecki, L. S. (1997). Budeanu and Fryze: *Two Frameworks for Interpreting Power Properties of Circuits with Nonsinusoidal Voltages and Currents*. Electrical Engineering. Vol. 80, pp.359-367.

Dimitrijevic, M. and Litovski, M. (2012). *Quantitative Analysis of Reactive Power Calculations for Small Non-linear Loads*. Proceedings of Small Systems Simulation Symposium, Nis, Serbia, 12-14 February, pp 150-154.

Dong, Y. et al. (2011). *Short-term Electricity Price Forecast based on the Improved Hybrid Model*. Energy Conversion and Management. Vol. 52, pp. 2987-2995.

Fan, G. F. et al. (2013). *Support Vector Regression Model Based on Empirical Mode Decomposition and Auto Regression for Electric Load Forecasting*. Energies. Vol. 6, pp. 1887-1901.

Fan, X. and Zhu, Y. (2010). *The Application of Empirical Mode Decomposition and Gene Expression Programming to Short-term Load Forecasting*. In: 2010 Sixth International Conference on Natural Computation, 10-12 Aug. Yantai. Vol 8, pp. 4331-4334.

Felice, M. D. *et al.* (2013). *Electricity Demand Forecasting over Italy: Potential Benefits using Numerical Weather Prediction Models*. Electric Power Systems Research. Vol. 104, pp. 71-79.

Feng, S. H. A. *et al.* (2013). *Based on the EMD and PSO-BP Neural Network of Short-term Load Forecasting*. Advanced Materials Research. Vol. 614- 615, pp.1872-1875.

George, C.S. *et al.* (2003). *Regression Analysis. Modeling and Forecasting*. USA: Graceway Publishing Company, Inc.

Ghelardoni, L. *et al.* (2013). *Energy Load Forecasting using Empirical Mode Decomposition and Support Vector Regression*. IEEE Transactions on Smart Grid. Vol. 4(1), pp.549-556.

Gilliland, M. (2010). *The Business Forecasting Deal. Exposing Myths, Eliminating Bad Practices, Providing Practical Solutions*. New Jersey: John Wiley and Sons Inc.

Hanke, J. E. *et al.* (2001). *Business Forecasting. Seventh Edition*. New Jersey: Prentice Hall.

Hofmann, W. *et al.* (2012). *Reactive Power Compensation. A Practical Guide*. United Kingdom: John Wiley & Sons Ltd.

Huang, N. E. *et al.* (1998). *The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-stationary Time Series Analysis*. Proceedings of the Royal Society of London. Mathematical, Physical and Engineering Sciences, Vol. 454, pp.903-995.

Huurman, C. *et al.* (2012). *The Power of Weather*. Computational Statistics and Data Analysis. Vol. 56, pp.3793-3807.

Hyndman, R. J. and Kostenko, A. V. (2007). Minimum Sample Size Requirements for Seasonal Forecasting Models. *Foresight* 6. 12-15.

Karuppanan, P. *et al.* (2011). *Fryze Power Theory with Adaptive-HCC based Active Power Line Conditioners*. International Conference on Power and Energy Systems (ICPS), Dec 22-24, IIT-Madras.

Kim, D. and Oh, H. S. (2009). *EMD: A Package for Empirical Mode Decomposition and Hilbert Spectrum*. The R Journal. Vol.1, pp.40-46.

Kim, M. S. (2013). *Modeling Special-Day Effects for Forecasting Intraday Electricity Demand*. European Journal of Operational Research. Vol. 230, pp. 170-180.

Kopsinis, Y. and McLaughlin, S. (2007). *Investigation of the Empirical Mode Decomposition based on Genetic Algorithm Optimization Schemes* in ICASSP.

Liu, N. *et al.* (2014). *Short-term Forecasting of Temperature Driven Electricity Load using Time Series and Neural Network Model*. Journal of Clean Energy Technologies. Vol. 2, pp.327-331.

Liu, Z. *et al.* (2010). *A New Short-term Load Forecasting Model of Power System based on HHT and ANN*. Lecture Notes Computer Science. Vol.6064, pp.448-454.

Liu, Z. *et al.* (2014). *A New Short-term Load Forecasting Method of Power System based on EEMD and SS-PSO*. Neural Computation & Application. Vol. 24, pp.973-983.

Makridakis, S. *et al.* (1998). *Forecasting. Methods and Application*. New York: John Willey and Sons.

Mohamed, N. (2011). *Parametric and Artificial Intelligence based Methods for Forecasting Short-term Electricity Load Demand*. Malaysia:UTM.

Mohamed, N. *et al.* (2011). *Improving Short-term Load Forecasting using Double Seasonal ARIMA Model*. World Applied Sciences. Vol. 15(2), pp.223-231.

Nunes, J. C. *et al.* (2003). *Image Analysis by Bidimensional Empirical Mode Decomposition*. Image and Vision Computing. Vol. 21, pp. 1019-1026.

Okolobah, V. A. (2014). *Electricity Peak Load Demand Forecast in a Deregulated Energy Market in Bida City of Nigeria*. Malaysia: UTM.

Okolobah, V. A. and Ismail, Z. (2013). *An Empirical Mode Decomposition Approach to Peak Load Demand Forecasting*. Indian Journal of Science and Technology. Vol. 6(9), pp.5201-5207

Okolobah, V. A. and Ismail, Z. (2013). *A New Approach to Peak Load Forecasting based on EMD and ANFIS*. Indian Journal of Science and Technology. Vol. 6(12), pp.5600-5606.

Okolobah, V. A. and Ismail, Z. (2013). *Forecasting Peak Load Demand by ARIMA and EMD Method*. Archives Des Sciences. Vol. 66, pp.1-15.

Pankratz, A. (1991). *Forecasting with Dynamic Regression Models*. Canada: John Wiley & Sons, Inc.

Rilling, G. (2007). *Decompositions Models Empirical*. French: ENS Lyon.

Rilling, G. and Flandrin, P. (2008). *One or Two Frequencies? The Empirical Mode Decomposition Answers*. IEEE Trans. On Signal Processing. Vol.56(1), pp. 85-95.

Steffensen, J. F. (2006). *Interpolation. Second Edition*. New York: Dover Publications, Inc.

Stellwagen, E. A. and Goodrich, R. L. (2010). *Forecast Pro XE Statistical Reference Manual*. USA: Business Forecast Systems, Inc.

Stellwagen, E.A and Goodrich, R. L. (2010). *Forecast Pro XE Users Guide*. USA: Business Forecast Systems, Inc.

Stoykova, E. *et al.* (2007). 3-d Time-varying Scene Capture Technologies-A Survey. *IEEE Transactions on Circuits and System for Video Technology*. Vol. 17(11), pp. 1568-1586.

Sun, W. *et al.* (2011). *Power System Load Forecasting based on EEMD and ANN*. *Lect. Notes Computer Science*. Vol. 6675, pp. 429-436.

Tagare, D. M. (2004). *Reactive Power Management*. New Delhi: Tata McGraw-Hill Publishing Company Limited.

Tenaga Nasional Berhad.(TNB).(2008). *Annual Report*.Malaysia: TNB.

Tenaga Nasional Berhad.(TNB).(2008). *Tariff Book*. Malaysia: TNB.

Tenaga Nasional Berhad.(TNB).(2012). *Electricity Supply Application Handbook*. Malaysia: TNB.

Tsakalozos, N. *et al.* (2012). A Formal Study of the Nonlinearity and Consistency of the Empirical Mode Decomposition. *Signal Processing*. Vol. 92, pp. 1961-1969.



Wang, B. *et al.* (2008). *A New ARMAX Model based on Evolutionary Algorithm and Particle Swarm Optimization for Short-term Load Forecasting*. *Electric Power Systems Research*. Vol. 78, pp.1679-1685.

Wang, H. *et al.* (2012). *Empirical Mode Decomposition on Surfaces*. *Graphical Models*. Vol. 74. Pp. 173-183.

Wang, Y. *et al.* (2010). *A Comparative Study on the Local Mean Decomposition and Empirical Mode Decomposition and Their Applications to Rotating Machinery Health Diagnosis*. *Journal of Vibration and Acoustics*. Vol. 132, pp. 021010-1 – 021010-10.

Wei, W. W. S. (2006). *Time Series Analysis. Univariate and Multivariate Methods, Second Edition*. Canada: Pearson Education, Inc.

Willems, J. L. (2011). *Budeanu's Reactive Power and Related Concepts Revisited*. *IEEE Transactions on Instrumentation and Measurement*. Vol.60(4), pp.1182-1186.

Wu, Z. and Huang, N. E. (2004). *A Study of the Characteristics of White Noise using the Empirical Mode Decomposition*. *Proceedings of the Royal Society of London. Mathematical, Physical and Engineering Sciences*, Vol. 460, pp.1597-1611.

Xiong, T. *et al.* (2014). *Does Restraining End Effect Matter in EMD-Based Modeling Framework for Time Series Prediction? Some Experimental Evidences*. *Neurocomputing*. Vol. 123, pp. 174-184.

Yan, X. and Chowdhury, N. A. (2013). *Mid-term Electricity Market Clearing Price Forecasting: A Hybrid LSSVM and ARMAX Approach*. *Electrical Power and Energy Systems*. Vol. 53, pp. 20-26.

Yang, Z. and Yang, Z. (2009). *A New Definition of the Intrinsic Mode Function*. *World Economy of Science, Engineering and Technology*. Vol. 3(12), pp.741-744.

Zhang, L. (2012). *A Novel Instantaneous Frequency Computation Approach for Empirical Mode Decomposition*. *World Academy of Science, Engineering and Technology*. Vol.6, pp.1730-1734.

Zhang, X. *et al.* (2008). *A New Approach for Crude Oil Price Analysis based on Empirical Mode Decomposition*. *Energy Economics*. Vol. 30, pp. 905-918.

Zheng, Y. and Qin, Z. (2009). *Region-based Image Fusion Method using Bidimensional Empirical Mode Decomposition*. *Journal of Electronic Imaging*. Vol 18(1), pp. 013008(1)-013008(10).

Zhou, X. *et al.* (2009). *Optical 3-D Shape Measurement for Dynamic Object using Color Fringe Pattern Projection and Empirical Mode Decomposition*. *Proc.Of SPIE*. Vol. 7389, pp. 73890D-1 – 73890D-9.

Zhu, X. *et al.* (2012). *A Hybrid Method for Short-term Load Forecasting in Power System*. In: *Proceedings of the 10<sup>th</sup> World Congress on Intelligent Control and Automation*. 6-8 July, 2012. Beijing, China.