NEW INPUT IDENTIFICATION AND ARTIFICIAL INTELLIGENCE BASED TECHNIQUES FOR LOAD PREDICTION IN COMMERCIAL BUILDING

AHMAD SUKRI BIN AHMAD

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Electrical Engineering)

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

AUGUST 2016

This thesis is dedicated to

my beloved late father, Ahmad bin Baba (*Al-Fatihah*),

my beloved mother, Salamah binti Abu Bakar,

my wife, Mrs. Syamimi binti Hashim

my brother and sisters for your love, perseverance and sacrifices.

Thank you very much.

ACKNOWLEDGEMENTS

ABSTRACT

The accuracy of prediction models for electrical loads are important as the predicted result can affect processes related to energy management such as maintenance planning, decision-making processes, as well as cost and energy savings. The studies on improving load prediction accuracy using Least Squares Support Vector Machine (LSSVM) are widely carried out by optimizing the LSSVM hyper-parameter which includes the Kernel parameter and the regularization parameter. However, studies on the effects of input data determination for the LSSVM have not widely tested by researchers. This research developed an input selection technique using Modified Group Method of Data Handling (MGMDH) to improve the accuracy of buildings load forecasting. In addition, a new cascaded Group Method of Data Handing (GMDH) and LSSVM (GMDH-LSSVM) model is developed for electrical load prediction to improve the prediction accuracy of LSSVM model. To further improve the prediction model ability, a Modified GMDH has been cascaded to the LSSVM model to enhance the accuracy of building electrical load prediction and reduce the complexity of GMDH model. The proposed models are compared with GMDH model, LSSVM model and Artificial Neural Network (ANN) model to observe the prediction performance. The performances of prediction for each tested models are evaluated using the Mean Absolute Percentage Error (MAPE). In this analysis, the proposed prediction model, gives 33.82% improvement of prediction accuracy as compared to LSSVM model. From this research, it can be concluded that cascading the models can improve the prediction accuracy and the proposed models can be used to predict building electrical loads.

ABSTRAK

Ketepatan model ramalan untuk beban elektrik adalah penting kerana keputusan diramalkan boleh memberi kesan kepada proses yang berkaitan dengan pengurusan tenaga seperti perancangan penyelenggaraan, proses membuat keputusan serta penjimatan kos dan tenaga. Kajian untuk meningkatkan ketepatan beban ramalan menggunakan Mesin Sokongan Vektor Kuasadua Terkecil (LSSVM) dijalankan secara meluas dengan mengoptimumkan parameter hiper LSSVM yang merangkumi parameter Kernel dan parameter regularisasi. Walau bagaimanapun, kajian tentang kesan penentuan data masukan bagi LSSVM tidak diuji secara meluas oleh penyelidik. Kajian ini membangunkan teknik pemilihan data masukan dengan menggunakan Kaedah Kumpulan Pengendalian Data Diubahsuai (MGMDH) untuk menambahbaik ketepatan peramalan beban bangunan. Selain itu, model Kaedah Kumpulan Pengendalian Data (GMDH) dan LSSVM (GMDH-LSSVM) bersiri yang baru telah dibangunkan untuk menambahbaik ketepatan peramalan model LSSVM. Untuk meningkatkan lagi keupayaan model ramalan, GMDH yang diubahsuai telah diletakkan secara bersiri dengan model LSSVM untuk menambahbaik ketepatan bangunan ramalan beban elektrik dan mengurangkan tahap kerumitan model GMDH. Model – model yang dicadangkan ini dibandingkan prestasi ramalannya dengan model GMDH, LSSVM dan Rangkaian Neural Buatan (ANN). Prestasi ramalan dinilai menggunakan Min Peratusan Ralat Mutlak (MAPE). Dalam analisis ini, model ramalan yang dicadangkan telah memberikan peningkatan ketepatan ramalan sebanyak 33.82% berbanding model LSSVM. Daripada penyelidikan ini, dapat disimpulkan bahawa model ramalan bersiri dapat menambahbaik ketepatan model ramalan dan model-model cadangan ini boleh digunakan untuk peramalan beban elektrik bangunan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AACO	-	Adaptive Ant Colony Optimization
AEMAS	-	ASEAN Energy Management Scheme
ANN	-	Artificial Neural Network
ARIMA	-	Auto Regressive Integrated Moving Average
ARIMAX	-	Auto Regressive Integrated Moving Average with Exogenous Variables
ARMA	-	Auto Regressive Moving Average
ARMAX	-	Auto Regressive Moving Average with Exogenous Variables
ASEAN	-	Association of South East Asian Nations
BEMS	-	Building Energy Management System
BPNN	-	Back-Propagation Neural Network
DE	-	Differential Evolution
FOA	-	Fly Optimization Algorithm
GA	-	Genetic Algorithm
GLSSVM	-	GMDH and LSSVM
GMDH	-	Group Method of Data Handling
GRNN	-	General Regression Neural Network
HVAC	-	Heating, Ventilation and Air-Conditioning System
kW	-	kilo Watt
kWh	-	kilo Watt hour
LSSVM	-	Least Square Support Vector Machine
LTLF	-	Long-Term Load Forecasting
MADA	-	Muda Agricultural Development Authority
MAPE	-	Mean Absolute Percentage Error
MELs	-	Miscellaneous Electrical Loads
MLR	-	Multiple Linear Regression

MMSE	-	Minimum Mean Square Error
MSE	-	Mean Squared Error
MTLF	-	Medium-Term Load Forecasting
PSO	-	Particle swarm optimization
QPSO	-	Quantum-behaved Particle Swarm Optimization
RBF	-	Radial Basis Function
RMSE	-	Root Mean Square Error
SEU	-	Significant Energy User
SLT	-	Statistic Learning Theory
SRM	-	Structural Risk Minimization
SSE	-	Sum of Squared Error
STLF	-	Short-Term Load Forecasting
SVM	-	Support Vector Machine
SVR	-	Support Vector Regression
TNB	-	Tenaga Nasional Berhad

LIST OF SYMBOLS

γ -   Regularization parameter

δ -   Kernel Parameter

Σ -   Summation

ω -   Weight vector

$\phi(x)$ -   Non-linear function

R   -   Correlation Coefficient

X^T -   Transverse of X

L   -   Lagrangian

ε -   Insensitive tube (SVM)

C   -   Error Cost

t_t -   t-test

β_i -   Coefficient of variables

S_{β_i} -   Estimated standard deviation of β_i

e -   Residual error

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background

The tremendous development of countries around the globe in recent years especially in the economic and industrial sectors has great impact on electrical energy consumption. Population growth and the demands of quality lifestyle also contribute significantly to the demand for electrical energy. Commercial buildings and residential areas are major electrical energy consumers and the efficient use of electrical energy in this sector can help to reduce energy demands and the environmental impact of electricity generation especially in the reduction of pollution, carbon footprint and greenhouse effects. Monitoring and auditing the use of electricity in buildings can also contribute to reducing energy consumption and energy cost.

It is for this reason that energy management plays an important role in saving energy and cost as well as reducing the negative impact to the environment. For energy management planning of buildings, the forecasting method is useful in predicting future scenarios of building loads based on current situation. The objective of building electrical load forecasting is to evaluate the building's electrical energy consumption and electrical load pattern so that good decisions can be made regarding energy cost, building design, maintenance and management planning. Evaluation is an important element in the analysis of electrical load patterns from a forecasting model. The accuracy of the forecasting results is important because of good decision can be made for a particular building based on the forecasting results. The use of forecasting techniques to find new information has increased due to the varieties of data available in our daily lives. Various forecasting techniques are used to analyze data and these techniques will be discussed in this thesis.

Based on previous studies, there are a variety of forecasting methods have been used. The implementation of forecasting methods using Artificial Intelligence and Soft Computing have helped in the development of this forecasting method. The studies on improving load forecasting accuracy using Least Square Support Vector Machine (LSSVM) are widely carried out by optimizing the LSSVM hyper-parameter which includes the Kernel parameter and the regularization parameter. However, studies on the effects of input data determination for the LSSVM are not widely tested by researchers. The selection of a suitable input data set plays an important role in determining the accuracy of the load forecasted by the LSSVM model. Thus, this research will look at the impact on the selection of input for LSSVM by using Group Method of Data Handling (GMDH) and Modified GMDH to forecast buildings' electrical load. This model has been used in dealing with uncertainty and linear or non-linear systems in many fields.

1.2 Problem Statement

Prediction accuracy in the electric load analysis is important issue since the prediction result will influence the decision making process and future planning. Therefore, the research on improving the prediction accuracy are continuously conducted. One of the factors that affects the prediction accuracy is the input determination. However, the emphasis on the selection of input to the prediction models are not much discussed, although it is important to determine the accuracy of forecasting model. Currently, prediction using Least Square Support Vector Machine (LSSVM) model has been widely implemented in many fields. However, the use of LSSVM models without aided with the appropriate input would lead to inaccurate prediction results. Hence, this research will improve the LSSVM model to make the prediction results more accurate. Additionally, the application of LSSVM in prediction of building electrical load has been widely used. In the input selection process using Group Method of Data Handling (GMDH) model, it has a tendency to produce more complex network. This will make the prediction accuracy disturbed due to the complexity developed. The problem statement stated above can be summarize into three points which are

    i.   The input selection for the prediction models are not much discussed, although it is important to determine the accuracy of forecasting model.

    ii.   LSSVM forecasting model without appropriate input would lead to inaccurate prediction results.

    iii.   The conventional GMDH method has a tendency to produce more complex network.

1.3 Objectives

The objectives of this research are

i. To develop input selection technique using Modified Group Method of Data Handling (MGMDH) for buildings load forecasting.

ii. To develop a new model termed as cascaded GMDH-LSSVM to solve buildings electrical load prediction accuracy.

iii. To propose Cascaded Modified GMDH-LSSVM structure for accuracy of electrical load prediction and reduce the complexity of GMDH model.

1.4 Scopes of Work

The scope and limitations of this research are as follows:

i. The analysis is limited to short-term load prediction analysis.

ii. Historical data for analysis are collected from a higher learning institution, which is in the commercial buildings category.

iii. Load analysis is limited to the assessment of electric energy consumption of the building.

iv. The LSSVM hyper-parameters used in Cascaded GMDH-LSSVM and Cascaded Modified GMDH-LSSVM are fixed in order to observe the effect of input data set of the forecasting results.

1.5   Significance of the Research

The research on prediction methods and its implementation in prediction building electrical loads can be useful to various parties such as the commercial building management. There are various methods of forecasting available including the single prediction method and also hybrid methods. This research was conducted to study the prediction accuracy performances of a hybrid method in prediction building electrical loads. In this research, an existing prediction method, the LSSVM model was cascaded with the GMDH and Modified GMDH model. The GMDH was used to determine the inputs and the LSSVM used the inputs to predict the time series of loads. Suitable input for prediction is important as it will provide accurate results in electrical load prediction. The analysis of load prediction for buildings can help building energy managers determine a building's electrical load patterns. By knowing the near future electrical load patterns, building energy managers can identify where, when, and how much energy will be used and able to plan on optimizing the electrical energy usage in buildings.

1.6   Thesis Organization

This thesis is organized in five main chapters.

Chapter 1 provides a brief overview of the research background including the problem statement, thesis objective, scope of work and significant of the research.

Chapter 2 addresses the literatures on the existing prediction methods in building load prediction and their importance to energy consumption planning activities. The brief of Energy Management and Building Electrical Loads also presented in this chapter.

Chapter 3 presents the methodology conducted in this research. The forecasting methods used in this research are presented which are the GMDH, Modified GMDH, Cascaded GMDH - LSSVM and Cascaded Modified GMDH - LSSVM.

Chapter 4 details out the prediction results from the tested models and the proposed model. The performance of the proposed model and the other models are compared based on the model accuracy and presented in tables and figures.

Chapter 5 provides the thesis conclusion with some recommendations for future works. This chapter also presented the research contribution at the end of this chapter.

REFERENCES

1.	Spann, M. and B. Skiera, *Internet-Based Virtual Stock Markets for Business Forecasting.* Management Science, 2003. 49(10): p. 1310-1326.

2.	Yao, J. and C.L. Tan, *A case study on using neural networks to perform technical forecasting of forex.* Neurocomputing, 2000. 34(1-4): p. 79-98.

3.	Panda, C. and V. Narasimhan, *Forecasting exchange rate better with artificial neural network.* Journal of Policy Making, 2007. 29(2): p. 227-236.

4.	Ince, H. and T.B. Trafalis, *A hybrid model for exchange rate prediction.* Decision Support Systems, 2006. 42(2): p. 1054-1062.

5.	Trafalis, T.B. and H. Ince. *Support Vector Machine for Regression and Applications to Financial Forecasting.* in *IEEE-INNS-ENNS International Joint Conference on Neural Networks (IJCNN'00).* 2000. Como, Italy: IEEE.

6.	Lee, R. and T. Miller, *An Approach to Forecasting Health Expenditures, with Application to the U.S. Medicare System.* HSR: Health Services Research, 2002. 37(5): p. 1365-1386.

7.	Channouf, N., et al., *The application of forecasting techniques to modeling emergency medical system calls in Calgary, Alberta.* Health Care Manage Sci, 2007. 10(1): p. 25-45.

8.	Montgomery, D.C., C.L. Jennings, and M. Kulahci, *Introduction to Time Series Analysis and Forecasting.* 2008: John Wiley & Sons.

9.	Witt;, S.F. and C.A. Witt, *Forecasting Tourism Demand: A Review of Empirical Research.* International Journal of Forecasting, 1995. 11: p. 447 - 475.

10.	McAleer, C.L.M., *Time Series Forecast of International Travel Demand of Australia.* Tourism Management, 2002. 23: p. 389 - 396.

11.	Enke, D. and S. Thawornwong, *The use of data mining and neural networks for forecasting stock market returns.* Expert Systems with Applications, 2005. 29(4): p. 927–940.

12.	Bond, S.R. and J.G. Cummins, *Uncertainty and investment: an empirical investigation using data on analysts' profits forecasts.* 2004, Federal Reserve Board (U.S.).

13.	Stevenson, W.J., *Forecasting*, in *Operation Management.* 2011, Mcgraw Hill: 2011.

14.	Niimura, T. *Forecasting Techniques for Deregulated Electricity Market Prices - Extended Survey.* in *Power Systems Conference and Exposition, 2006. PSCE '06. 2006 IEEE PES.* 2006. Atlanta, GA: IEEE.

15.	R. Samsudin, P.Saad, and A. Shabri, *River flow time series using least squares support vector machines.* Hydrology and Earth System Sciences, 2011. 15(6): p. 1835-1852.

16.	Xia, C., J. Wang, and K. McMenemy, *Short, medium and long term load forecasting model and virtual load forecaster based on radial basis function neural networks.* Electrical Power and Energy Systems, 2010. 32(7).

17.	Hahn, H., S. Meyer-Nieberg, and S. Pickl, *Electric Load Forecasting Methods: Tools for decision making.* European Journal of Operaional Research, 2009. 199(3): p. 902-907.

18. Zhao, H.-x. and F. Magoulès, *A review on the prediction of building energy consumption.* Renewable and Sustainable Energy Reviews, 2012. 16(6): p. 3586 - 3592.

19. Kyriakides, E. and M. Polycarpou, *Short Term Electric Load Forecasting: A Tutorial.* Studies in Computational Intelligence, 2007. 35: p. 391-418.

20. Yang, J., *Power System Short-Term Load Forecasting.* 2006.

21. Muhtazaruddin, M.N., *Short-Term Load Forecasting Via Artificial Neural Network.* 2010, Universiti Teknologi Malaysia: Skudai. p. 75.

22. Romera, E.G., M.A. Jaramillo-Moran, and D. Carmona-Fernandez, *Monthly Electric Energy Demand Forecasting Based on Trend Extraction.* IEE Transactions on Power System, 2006. 21(4): p. 1946.

23. Song, K.-B., et al., *Hybrid Load Forecasting Method With Analysis of Temperature Sensitivities.* IEEE Transactions on Power System, 2006. 21(2): p. 869.

24. Aguirre, L.A., et al., *Dynamical prediction and pattern mapping in short-term load forecasting.* Electrical Power and Energy Systems, 2008. 30.

25. Truong, N.-V., L. Wang, and P.K.C. Wong, *Modelling and short-term forecasting of daily peak power demand in Victoria using two-dimensional wavelet based SDP models.* Electric Power and Energy System, 2008. 30(p. 511-518).

26. Bhattacharyya, S.C. and L.T. Thanh, *Short-term electric load forecasting using an artificial neural network: case of Northern Vietnam.* International Journal of Energy Research, 2004. 28: p. 436-472.

27. Nengling, T., J.u. Stenzel, and W. Hongxiao, *Techniques of applying wavelet transform into combined model for short-term load forecasting.* Electric Power Systems Research, 2006. 76: p. 525-533.

28. Senjyu, T., et al., *One-Hour-Ahead Load Forecasting Using Neural Network.* IEE Transactions on Power System, 2002. 17(1): p. 113.

29. Ling, S.H., et al., *Short-Term Electric Load Forecasting Based on a Neural Fuzzy Network.* IEEE Transactions on Industrial Electronics, 2003. 50(6).

30. Papalexopoulos, A.D. and T.C. Hesterberg, *A Regression-Based Approach To Short-Term System Load Forecasting.* IEEE Transactions on Power System, 1990. 5(4): p. 1535.

31. Yang, J. and J. Stenzel, *Short-term load forecasting with increment regression tree.* Electric Power Systems Research, 2006. 76: p. 880.

32. Pandian, S.C., et al., *Fuzzy approach for short term load forecasting.* Electric Power Systems Research, 2006. 76.

33. Al-Kandari, A.M., S.A. Soliman, and M.E. El-Hawary, *Fuzzy short-term electric load forecasting.* Electrical Power and Energy Systems, 2004. 26.

34. Kandil, N., et al., *An efficient approach for short term load forecasting using artificial neural networks.* Electrical Power and Energy Systems, 2006. 28: p. 525.

35. Ranaweera, D.K., G.G. Karady, and R.G. Farmer, *Economic impact analysis of load forecasting.* IEEE Transactions on Power System, 1997. 12(3): p. 1388.

36. Ghiassi, M., D.K. Zimbra, and H. Saidane, *Medium term system load forecasting with a dynamic artificial neural network model.* Electric Power Systems Research, 2006. 76(5): p. 302-316.

37. Pai, P.-F. and W.-C. Hong, *Forecasting regional electricity load based on recurrent support vector machines with genetic algorithms.* Electric Power Systems Research, 2005. 74(3): p. 417-425.

38. Al-Hamadi, H.M. and S.A. Soliman, *Long-term/mid-term electric load forecasting based on short-term correlation and annual growth.* Electric Power Systems Research, 2005. 74.

39. Feinberg, E.A. and D. Genethliou, *Load Forecasting*, in *Applied Mathematics for Restructured Electric Power Systems.* 2005, Springer Link. p. 269-285.

40. Kermanshahi, B. and H. Iwamiya, *Up to year 2020 Load Forecasting using neural nets.* Electric Power and Energy System, 2002. 24: p. 789.

41. Carpinteiro, O.a.A.S., et al., *Long-term load forecasting via a hierarchical neural model with time integrators.* Electric Power Systems Research, 2007. 77(3 - 4): p. 371 - 378.

42. Hu, Z., Y. Bao, and T. Xiong, *Comprehensive learning particle swarm optimization based memetic algorithm for model selection in short-term load forecasting using support vector regression.* Applied Soft Computing, 2014. 25: p. 15 - 25.

43. Saab, S., E. Badrb, and G. Nasra, *Univariate modeling and forecasting of energy con-sumption: the case of electricity in Lebanon.* Energy, 2001. 26(1).

44. Goia, A., C. May, and G. Fusai, *Functional clustering and linear regression for peak load forecasting.* International Journal of Forecasting, 2010. 26(4).

45. Amarawickrama, H.A. and L.C. Hunt, *Electricity demand for Sri Lanka: A time series analysis.* Energy, 2008. 33(5).

46. Srinivasan, D., et al., *Parallel neural network-fuzzy expert system strategy for short-term load forecasting: system implementation and performance evaluation.* Power Systems, IEEE Transactions, 1999.

47. Khotanzad, A., E. Zhou, and H. Elragal, *A neuro-fuzzy approach to short-term load forecasting in a price-sensitive environment.* Power Systems, IEEE Transactions, 2002. 17(4).

48. Goude, Y., R. Nedellec, and N. Kong, *Local Short and Middle Term Electricity Load Forecasting With Semi-Parametric Additive Models.* Smart Grid, IEEE Transactions, 2014. 5(1).

49. Paparoditis, E. and T. Sapatinas, *Short-Term Load Forecasting: The Similar Shape Functional Time-Series Predictor.* Power Systems, IEEE Transactions, 2013. 28(4): p. 3818 - 3825.

50. Mandal, P., et al., *A neural network based several-hour-ahead electric load forecasting using similar days approach.* International Journal of Electrical Power & Energy Systems, 2006. 28(6): p. 367 - 373.

51. Kulkarni, S., S.P. Simon, and K. Sundareswaran, *A spiking neural network (SNN) forecast engine for short-term electrical load forecasting.* Applied Soft Computing, 2013. 13(8): p. 3628–3635.

52. Niu, D.-x., H.-f. Shi, and D.D. Wu, *Short-term load forecasting using bayesian neural networks learned by Hybrid Monte Carlo algorithm.* Applied Soft Computing, 2012. 12(6): p. 1822–1827.

53. Quan, H., D. Srinivasan, and A. Khosravi, *Short-term load and wind power forecasting using neural network-based prediction intervals.* IEEE Transactions On Neural Networks And Learning Systems, 2012. 25(2): p. 303 - 315.

54. Chen, B.-J., M.-W. Chang, and C.-J. Lin, *Load forecasting using support vector Machines: a study on EUNITE competition 2001.* IEEE TRANSACTIONS ON POWER SYSTEMS, 2004. 19(4).

55. Elattar, E.E., J. Goulermas, and Q.H. Wu, *Electric Load Forecasting Based on Locally Weighted Support Vector Regression.* Systems, Man, and Cybernetics,

Part C: Applications and Reviews, IEEE Transactions on, 2010. 40(4): p. 438-447.

56. Selakov, A., et al., *Hybrid PSO–SVM method for short-term load forecasting during periods with significant temperature variations in city of Burbank.* Applied Soft Computing, 2014. 16.

57. Nagi, J., et al., *A computational intelligence scheme for the prediction of the daily peak load.* Applied Soft Computing, 2011. 11(8).

58. Ceperic, E., V. Ceperic, and A. Baric, *A Strategy for Short-Term Load Forecasting by Support Vector Regression Machines.* Power Systems, IEEE Transactions, 2013. 28(4).

59. Ghelardoni, L., M. Alessandro Ghio, and D. Anguita, *Energy Load Forecasting Using Empirical Mode Decomposition and Support Vector Regression.* IEEE Transactions on Smart Grid, 2013. 4(1).

60. Xiong, T., Y. Bao, and Z. Hu, *Interval forecasting of electricity demand: A novel bivariate EMD-based support vector regression modeling framework.* International Journal of Electrical Power & Energy Systems, 2014. 63.

61. Zivanovic, R., *Local Regression-Based Short-Term Load Forecasting.* Journal of Intelligent and Robotic Systems, 2001. 31(1-3): p. 115-127.

62. Hor, C.-L., S.J. Watson, and S. Majithia, *Analyzing the Impact of Weather Variables on Monthly Electricity Demand.* IEEE Transactions On Power Systems, 2005. 20(4): p. 2078 - 2085.

63. Bruhns, E., G. Deurveilher, and J.-s. Roy. *A Non-Linear Regression Model For Mid-Term Load Forecasting And Improvements In Seasonality.* in *15th Power Systems Computation Conference.* 2005.

64. Arunesh Kumar Singh, I., S. Khatoon, Md. Muazzam , D. K. Chaturvedi. *Load forecasting techniques and methodologies: A review.* in *2012 2nd International Conference on Power, Control and Embedded Systems.* 2012. Allahabad: IEEE.

65. Moghram, I. and S. Rahman, *Analysis And Evaluation Of Five Short-Term Load Forecasting Techniques.* IEEE Transactions on Power System, 1989. 4(4).

66. Barakat, E.H., et al., *Short-Term Peak Demand Forecasting I N Fast Developing Utility With Inherit Dynamic Load Characteristics.* IEEE Transactions on Power System, 1990. 5(3): p. 813 - 824.

67. Islam, B.U., *Comparison of Conventional and Modern Load Forecasting Techniques Based on Artificial Intelligence and Expert Systems.* International Journal of Computer Science Issue, 2011. 8(5).

68. papalexopoulos, A.D., S. Hao, and T.-M. Pen, *An Implementation Of A Neural Network Based Load Forecasting Model For The Ems* IEEE Transactions on Power Systems, 1994. 9(4).

69. Taylor, J.W., L.M.d. Menezes, and P.E. McSharry, *A comparison of univariate methods for forecasting electricity demand up to a day ahead.* International Journal of Forecasting, 2006. 22(1).

70. Brockwell, P.J. and R.A. Davis, *Time Series: Theory and Methods.* Springer Series in Statistics. 1991: Springer.

71. Barakat, E.H., J.M. Al-Qassim, and S.A. Al Rashed, *New model for peak demand forecasting applied to highly complex load characteristics of a fast developing area.* Generation, Transmission and Distribution, IEE Proceedings C, 1992. 139(2): p. 136 - 140.

72.   Chen, J.-F., W.-M. Wang, and C.-M. Huang, *Analysis of an adaptive time-series autoregressive moving-average (ARMA) model for short-term load forecasting.* Electric Power Systems Research, 1995. 34(3): p. 187 - 196.

73.   Behbahani, M.V.M.E.B.S.M.R., *Parameters Estimate of Autoregressive Moving Average and Autoregressive Integrated Moving Average Models and Compare Their Ability for Inflow Forecasting.* Journal of Mathematics and Statistics, 2012. 8(3): p. 330-338.

74.   Amjady, N., *Short-term hourly load forecasting using time-series modeling with peak load estimation capability.* IEEE Transactions On Power Systems, 2001. 16(4): p. 798 - 805.

75.   Pao, H.T., *Forecasting energy consumption in Taiwan using hybrid nonlinear models.* Energy and Buildings, 2009. 34(10): p. 1438-1446.

76.   Al-Homoud, M.S., *Computer-aided building energy analysis techniques.* Building and Environment, 2001. 36(4): p. 421-433.

77.   White, J.A. and H. Reichmuth. *Simplified Method For Predicting Building Energy Consumption Using Average Monthly Temperatures*. in *31st Intersociety Energy Conversion Engineering Conference*. 1996.

78.   Fernando Simon Westphal and Roberto Lamberts, *The use of simplified weather data to estimate thermal loads of non-residential buildings.* Energy and Buildings, 2004. 36(8): p. 847-854.

79.   Runming Yao and K. Steemers, *A method of formulating energy load profile for domestic buildings in the UK.* Energy and Buildings, 2005. 37(6): p. 663-671.

80.   Andrew Rice, Simon Hay, and D. Ryder-Cook. *A Limited-Data Model Of Building Energy Consumption*. in *2nd ACM workshop on embedded sensing systems for energy-efficiency in buildings*. 2010.

81.   Charles S. Barnaby and J.D. Spitler, *Development of the Residential Load Factor Method for Heating and Cooling Load Calculations.* ASHRAE, 2005. 111(1).

82.   Shengwei Wang and X. Xu, *Simplified building model for transient thermal performance estimation using GA-based parameter identification.* International Journal of Thermal Sciences, 2006. 45(4): p. 419-432.

83.   F. W. H. Yik, J. Burnett., and I. Prescott, *Predicting air-conditioning energy consumption of a group of buildings using different heat rejection methods.* Energy and Buildings, 2001. 33(2): p. 151-166.

84.   M. Bauer and J.L. Scartezzini, *Simplified Correlation Method Accounting for Heating and Cooling Loads in Energy-Efficient Buildings.* Energy and Buildings, 1998. 27(2): p. 147-154.

85.   Westergren., K.-E., H. Högberg, and U. Norlén, *Monitoring energy consumption in single-family houses.* Energy and Buildings, 1999. 29(3): p. 247-257.

86.   Pfafferott, J., S. Herkel, and J. Wapler, *Thermal Building Behaviour in Summer: Long-Term Data Evaluation Using Simplified Models.* Energy and Buildings, 2005. 37(8): p. 844-852.

87.   Fei Lei and Pingfang Hu, *A Baseline Model for Office Building Energy Consumption in Hot Summer and Cold Winter Region*, in *International Conference on Management and Service Science, 2009. MASS '09. .* 2009: Wuhan. p. 1-4.

88.   Yuan Ma, et al., *Study on Power Energy Consumption Model for Large-Scale Public Building*, in *2nd International Workshop on Intelligent Systems and Applications (ISA), 2010* 2010: Wuhan. p. 1-4.

89.   Cho, S.-H., et al., *Effect of length of measurement period on accuracy of predicted annual heating energy consumption of buildings.* Energy Conversion and Management, 2004. 45(18-19): p. 2867-2878.

90.   Guy R. Newsham and B.J. Birt, *Building-level occupancy data to improve ARIMA-based electricity use forecasts*, in *2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings (BuildSys 2010).* 2010: Zurich, Switzerland. p. 13-18.

91.   Hoffman, A.J. *Peak demand control in commercial buildings with target peak adjustment based on load forecasting.* in *IEEE International Conference on Control Applications.* 1998. Trieste, Italy: IEEE.

92.   Aydinalp-Koksal, M. and V.I. Ugursal, *Comparison of Neural Network, Conditional Demand Analysis, and Engineering Approaches for Modeling End-Use Energy Consumption in the Residential Sector.* Applied Energy, 2008. 85(4): p. 271-296.

93.   Chen, K. and S.H. Kung, *Synthesis of Qualitative and Quantitative Approaches to Long Range Forecasting.* Technological Forecasting and Social Change, 1984. 26(3): p. 255-266.

94.   Saab, S., E. Badr, and G. Nasr, *Univariate modeling and forecasting of energy consumption: the case of electricity in Lebanon.* Energy and Buildings, 2001. 26(1): p. 1-14.

95.   Ben-Nakhi, A.E. and M.A. Mahmoud, *Cooling load prediction for buildings using general regression neural networks.* Energy Conversion and Management, 2004. 45(13-14): p. 2127-2141.

96.   Cheng-wen, Y. and Y. Jian, *Application of ANN for the Prediction of Building Energy Consumption at Different Climate Zones with HDD and CDD*, in *International Conference on Future Computer and Communication (ICFCC) 2010.* 2010: Wuhan. p. 286 - 289.

97.   Yokoyama, R., T. Wakui, and R. Satake, *Prediction of energy demands using neural network with model identification by global optimization.* Energy Conversion and Management, 2009. 50(2): p. 319-327.

98.   Merih Aydinalp, V. Ismet Ugursal, and A.S. Fung, *Modeling of the appliance, lighting, and spacecooling energy consumptions in the residential sector using neural networks.* Applied Energy, 2002. 71(2): p. 87-110.

99.   Merih Aydinalp, V. Ismet Ugursal, and A.S. Fung, *Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks.* Applied Energy, 2004. 79(2): p. 159-178.

100.   Nizami, S.J. and A.Z. Al-Garni, *Forecasting electric energy consumption using neural networks.* Energy Policy, 1995. 23(12): p. 1097-1104.

101.   Pedro A. Gonzalez and J.M. Zamarreno, *Prediction of hourly energy consumption in buildings based on a feedback artificial neural network.* Energy and Buildings, 2005. 37(6): p. 595-601.

102.   A. Azadeh, S.F. Ghaderi, and S. Sohrabkhani, *Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors.* Energy Conversion and Management, 2008. 49(8): p. 2272-2278.

103.   S. L. Wong, Kevin K. W. Wan, and T.N.T. Lam, *Artificial neural networks for energy analysis of office buildings with daylighting.* Applied Energy, 2010. 87(2): p. 551-557.

104.   Naoyuki KUBOTA, S.H., Fumio KOJIMA, and Kazuhiko TANIGUCHI. *GP-preprocessed fuzzy inference for the energy load prediction*. in *Proceedings of the Evolutionary Computation, 2000*. 2000. La Jolla, CA.

105.   Zhijian Hou, et al., *Cooling-loadprediction by the combination of roughsettheory and an artificial neural-network based on data-fusion technique*. Applied Energy, 2006. 83(9): p. 1033-1046.

106.   Shawe-Taylor;, J. and N. Cristianini, *Kernel Methods for Pattern Analysis*. 2004: Cambridge University Press.

107.   Horváth, *Support Vector Machine*. Springer Verlag, 2003.

108.   Li Xuemei, et al. *Building Cooling Load Forecasting Model Based on LS-SVM*. in *Information Processing, 2009. APCIP 2009. Asia-Pacific Conference on*. 2009.

109.   Dong, B., C. Cao, and S.E. Lee, *Applying support vector machines to predict building energy consumption in tropical region*. Energy and Buildings, 2005. 37(5): p. 545-553.

110.   Qiong Li, et al., *Applying support vector machine to predict hourly cooling load in the building*. Applied Energy, 2009. 86(10): p. 2249-2256.

111.   Zhijian Hou and Z. Lian, *An Application of Support Vector Machines in Cooling Load Prediction*, in *International Systems and Application 2009*. 2009: Wuhan. p. 1-4.

112.   Florance Lai, Frederic Magoules, and F. Lherminier, *Vapnik's learning theory applied to energy consumption forecasts in residential buildings*. International Journal of Computer Mathematics, 2008. 85(10): p. 1563-1588.

113.   Qiong Li, Peng Ren, and Qinglin Meng, *Prediction model of annual energy consumption of residential buildings*, in *IEEE International Conference on Advances in Energy Engineering*. 2010. p. 223-226.

114.   Xing-Ping, Z. and G. Rui, *Electrical energy consumption forecasting based on cointegration and a support vector machine in China*. WSEAS Trans. Math., 2007. 6(12): p. 878-883.

115.   Nagi, J., et al. *Detection of abnormalities and electricity theft using genetic Support Vector Machines*. in *TENCON 2008 - 2008 IEEE Region 10 Conference*. 2008.

116.   Wang, J., et al., *An annual load forecasting model based on support vector regression with differential evolution algorithm*. Applied Energy, 2012. 94(94).

117.   Robio, G., et al., *A heuristic method for parameter selection in LSSVM: Application to time series prediction*. International Journal of Forecasting, 2011. 27.

118.   Suykens, J.A.K. and J. Vandewalle, *Least Squares Support Vector Machine Classifiers*. Neural Process. Lett, 1999. 9(3): p. 293-300.

119.   Espinoza, M., J.A.K. Suykens, and B.D. Moor, *Load Forecasting Using Fixed-Size Least Squares Support Vector Machines*, in *Computational Intelligence and Bioinspired Systems*. 2005, Springer Berlin Heidelberg.

120.   Wu Junfang and N. Dongxiao. *Short Term Power Load Forecasting Using Least Squares Support Vector Machines*. in *2009 Second International Workshop on Computer Science and Engineering*. 2009. Qingdao.

121.   Wang Yi and L. Ying, *Applying LS-SVM to Predict Primary Energy Consumption*, in *International Conference on E-Product E-Service and E-Entertainment (ICEEE)*. 2010: Henan. p. 1-4.

122. Božić, M., M. Stojanović, and Z. Stajić, *Short-Term Electric Load Forecasting Using Least Square Support Vector Machines.* Facta Universitatis, 2010. 9(1): p. 141 - 150.

123. Yuansheng HUANG and J. DENG, *Short-term Load Forecasting with LS-SVM Based on Improved Ant Colony Algorithm Optimization.* Journal of Computational Information Systems, 2010. 6(5): p. 1431-1438.

124. Li, H., et al., *Annual Electric Load Forecasting by a Least Squares Support Vector Machine with a Fruit Fly Optimization Algorithm.* Energies, 2012. 5.

125. Xiaohui, L. and D. Qian. *Application of LS-SVM in the Short-term Power Load Forecasting Based on QPSO.* in *International Conference on Logistics Engineering, Management and Computer Science*. 2014. Atlantis Press.

126. Suykens, J.A.K. and J. Vandewalle, *Recurrent Least Squares Support Vector Machines.* IEEE Transactions On Circuits And Systems, 2000. 47(7): p. 1109 - 1114.

127. Suykens, J.A.K., J. Vandewalle, and B.D. Moor, *Optimal control by least squares support vector machines.* Neural Network, 2001. 14.

128. Suykens, J.A.K. *Nonlinear Modelling and Support Vector Machines*. in *IEEE Instrumentation and Measurement Technology Conference*. 2001. Budapest, Hungary: IEEE.

129. Shen, W., et al., *Forecasting stock indices using radial basis function neural networks optimized by artificial fish swarm algorithm.* Knowledge-Based Syste,, 2011. 24.

130. Zhang, Q., et al., *A Fuzzy Group Forecasting Model Based on Least Squares Support Vector Machine (LS-SVM) for Short-Term Wind Power.* Energies, 2012. 5.

131. Tan, G., et al., *Prediction of water quality time series data based on least squares support vector machine.* Procedia Engineering, 2012. 31.

132. Cheng, M.-Y., N.-D. Hoang, and Y.-W. Wu2, *Hybrid intelligence approach based on LS-SVM and Differential Evolution for construction cost index estimation: A Taiwan case study.* Automation in Construction, 2013. 35.

133. Onwubolu, G., *Hybrid Self-Organizing Modeling Systems*. 2009: Springer-Verlag Berlin Heidelberg.

134. Srinivasan, D., *Energy Demand Prediction Using GMDH Networks.* Neurocomputing, 2008. 72(1-3): p. 625-629.

135. Fan Li, Belle R. Upadhyaya, and L.A. Coffey, *Model-based monitoring and fault diagnosis of fossil power plant process units using Group Method of Data Handling.* ISA Transactions, 2009. 48(2): p. 213-219.

136. Hongya Xu, et al., *Application of GMDH to Short Term Load Forecasting.* Advanced in Intelligent System, 2012. 138: p. 27-32.

137. Ehab. E. Elattar and J.Y. Goulermas, *Generalized Locally Weighted GMDH for Short Term Load Forecasting.* IEEE Transactions On Systems, Man, And Cybernetics—Part C: Applications And Reviews, 2012. 42(3): p. 345-356.

138. Ruhaidah Samsudin, Puteh Saad, and A. Shabri, *The GMDH Model and Its Application to Forecasting of Rice Yields.* Jurnal Teknologi Maklumat, 2008. 20(4): p. 113-123.

139. Ruhaidah Samsudin and P. Saad. *A Time Series Forecasting Model Using Group Method Of Data Handling*. 2009.

140. Ruhaidah Samsudin, Puteh Saad, and Ani Shabri, *Combination of Forecasting Using Modified GMDH and Genetic Algorithm.* International Journal of

Computer Information Systems and Industrial Management Applications (IJCISIM), 2009. 1: p. 170-176.

141. Ruhaidah Samsudin, Puteh Saad, and Ani Shabri, *Hybridizing GMDH and Least Squares SVM Support Vector Machine for Forecasting Tourism Demand.* International Journal of Research and Reviews in Applied Sciences, 2010. 3(3): p. 274-279.

142. Samsudin, R., *Enhanced Group Method of Data Handling Models for Time Series Forecasting*, in *Faculty of Computing*. 2012, UTM.

143. Drezga;, I. and s. Rahman, *INPUT VARIABLE SELECTION FOR ANN-BASED SHORT-TERM LOAD FORECASTING.* IEEE Transactions on Power Systems, 1998. 13(4): p. 1238.

144. Mahmoud;, T., et al. *Load Demand Forecasting: Model Inputs Selection*. in *2011 IEEE Innovative Smart Grid Technologies Asia*. 2011. Perth, Australia: IEEE.

145. El-Keib, A.A., X. Ma, and H. Ma, *Advancement of statistical based modeling techniques for short-term load forecasting.* Electric Power Systems Research, 1995. 35.

146. Mbamalu, G.A.N. and M.E. El-Hawary, *Load Forecasting Via Suboptimal Seasonal Autoregressive Models And Iteratively Reweighted Least Squares Estimation.* IEEE Transactions on Power Systems, 1993. 8(1): p. 343-348.

147. Sindhav, I.B. and K. Khatua, *Short-term Load Forecasting using traditional demand forecasting.* IOSR Journal of Electrical and Electronics Engineering, 2015. 10(1).

148. Abdelaziz, E.A., R. Saidur, and S. Mekhilef, *A review on energy saving strategies in industrial sector.* Renewable and Sustainable Energy Reviews, 2011. 15(1): p. 150-168.

149. Kannan, R. and W. Boie, *Energy management practices in SME - Case study of a bakery in Germany.* Energy Conversion and Management, 2003. 44(6): p. 945-959.

150. Doukas, H., et al., *Intelligent building energy management system using rule sets.* Building and Environment, 2007. 42(10): p. 3562-3569.

151. Vikhorev, K., R. Greenough, and N. Brown, *An advanced energy management framework to promote energy awareness.* Journal if Cleaner Production, 2013. 43: p. 103-112.

152. Dounis, A.I., *Artificial intelligence for energy conservation in buildings.* Advances in Building Energy Research, 2010. 4(1): p. 267-299.

153. AEMAS. *AEMAS Objectives*. 2011 [cited 2014 12/03/2014]; Available from: http://www.aemas.org/node/2.

154. Dept. of Statistic, M., *Montly Statistical Bulletin*. 2012.

155. Smith, M., et al., *Energy transformed: sustainable energy solutions for climate change mitigation*. 2007. p. 6.

156. L. Suganthi and Anand A. Samuel, *Energy Models for Demand Forecasting - A Review.* Renewable and Sustainable Energy Reviews, 2012. 16(2): p. 1223-1420.

157. Dell, R.M. and D.A.J. Rand, *Energy storage — a key technology for global energy sustainability.* Journal of Power Sources, 2001. 100: p. 2-17.

158. Agency, U.S.E.P., *Buildings and their Impact on the Environment: A Statistical Summary*. 2009.

159.   Zografakis, N., K. Karyotakis, and K.P. Tsagarakis, *Implementation conditions for energy saving technologies and practices in office buildings: Part 1. Lighting.* Renewable and Sustainable Energy Reviews, 2012. 16(6): p. 4165-4174.

160.   Pe´rez-Lombard, L., J. Ortiz, and C. Pout, *A review on buildings energy consumption information.* Energy and Buildings, 2008. 40(3): p. 394-398.

161.   Berhad, T.N. *Pricing and Tariff.* 2012 [cited 2012 14 May 2012]; Available from: http://www.tnb.com.my/residential/pricing-and-tariff.html.

162.   Aun, C.S., *Energy Efficiency: Designing Low Energy Buildings Using Energy 10.* 2004, Pertubuhan Arkitek Malaysia.

163.   Ekici, B.B. and U.T. Aksoy, *Prediction of Building Energy Consumption by Using Artificial Neural Networks.* Advanced in Engineering Software, 2009. 40(5): p. 356-362.

164.   Omer, A.M., *Energy, environment and sustainable development.* Renewable and Sustainable Energy Reviews, 2008. 12(9): p. 2265-2300.

165.   Santamouris, M. and E. Dascalaki, *Passive Retrofitting of Office Buildings to Improve Their Energy Performance and Indoor Environment : the OFFICE project.* Building and Environment, 2002. 37(6): p. 575-578.

166.   Orosa, J.A. and A.C. Oliveira, *Energy saving with passive climate control methods in Spanish office buildings.* Energy and Buildings, 2009. 41(8): p. 823-828.

167.   Saidur, R., *Energy consumption, energy savings, and emission analysis in Malaysian office buildings.* Energy Policy, 2009. 37(10): p. 4104-4113.

168.   Yang, L., J.C. Lam, and C.L. Tsang, *Energy performance of building envelopes in different climate zones in China.* Applied Energy, 2008. 85(9): p. 800-817.

169.   Kelsey, J., *Updated Procedures for Commercial Building Energy Audits.* 2011, ASHRAE.

170.   Suykens;, J.A.K., et al., *Least Squares Support Vector Machines.* 2002.