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

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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.

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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.

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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
ϕ(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

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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.

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