LOAD SCHEDULING FOR SMART HOME USING DAY-AHEAD PREDICTION FROM ARTIFICIAL NEURAL NETWORK (ANN)

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DEDICATION

This thesis is dedicated to both of my parents who have always believing in me and support me throughout this journey. Not to forget the rest of my family, my supervisor and friends for helping me directly and indirectly in successfully completing this project. Sincere appreciation to all.

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ABSTRACT

Artificial Neural Network (ANN) in Mixed-Integer Linear Programming (MILP) technique for load scheduling of appliances in a single smart home system. This proposed method is achieved through backpropagation method of ANN tools in MATLAB which is the central mechanism by which neural networks learn to predict the next day load consumption of a home and promptly inserting the output to the MILP which would optimize the process of load scheduling. The integration of ANN with MILP can contribute to the precision of load scheduling. Having said that, to obtain the day ahead energy consumption, the annual data of the home is extract and injected in ANN as input and target classes. Hence, with the process of backpropagation, energy consumption is predicted while taking into consideration the Mean Squared Error (MSE) of the model. This prediction is then incorporated in the programming of MILP for optimization of load scheduling. The performance of the model is then evaluated by comparing before and after the optimization process. A total load of the appliance has been reduced from 51.24 kW/day to 44.84 kW/day. Furthermore, the overall cost of the electricity bill has been reduced from $3.98/day to $2.45/day. Therefore, the deduction of 38.44% of electricity bills makes the proposed method notably applicable and best to use in real time situation

ABSTRAK

Kajian ini mencadangkan penggunaan ramalan beban menggunakan Rangkaian Neural Buatan (ANN) dalam teknik Pemodelan Bersama-Integer Linear (MILP) untuk penjadualan beban peralatan dalam sistem rumah pintar tunggal. Kaedah yang dicadangkan ini dicapai melalui kaedah *"backpropagation"* alat ANN di MATLAB yang merupakan mekanisme utama yang mana rangkaian saraf belajar untuk meramalkan penggunaan beban keesokan hari sesebuah rumah dan memasukkan input ke MILP yang akan mengoptimumkan proses penjadualan beban. Kelebihan utama kaedah penyepaduan ini adalah ketepatan penjadualan profil beban dan tahap kesukaran untuk memahami yang jauh lebih mudah berbanding dengan algoritma lain. Untuk mendapatkan penggunaan tenaga pada keesokkan harinya, data tahunan rumah adalah ekstrak dan disuntik dalam ANN sebagai kelas input dan sasaran. Oleh itu, dengan proses "*backpropagation"*, penggunaan tenaga diramalkan semasa mengambil kira Regraman Mean Squared (MSE) model. Ramalan ini kemudiannya dimasukkan dalam pengaturcaraan MILP untuk mengoptimumkan penjadualan beban. Prestasi model kemudiannya dinilai dengan membandingkan sebelum dan selepas proses pengoptimuman. Telah dijumpai bahawa perbandingan perbandingan antara sebelum dan selepas penjadualan telah dibincangkan. Kesemua beban perkakas telah dikurangkan dari 51.24 kW/hari menjadi 44.84 kW/hari. Selain itu, kos keseluruhan bil elektrik telah dikurangkan dari $ 3.98/hari menjadi $ 2.45/hari. Oleh itu, potongan 38.44% bil elektrik menjadikan kaedah yang dicadangkan untuk dipakai dan sesuai untuk digunakan dalam keadaan sebenar

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
AMPL	-	A Mathematical Programming Language
EU	-	European Union
FERC	-	Federal Energy Regulatory Commission
GASC	-	Genetic Algorithm Superclustering
HEMS	-	Home Energy Management System MI
HFNN	-	Hybrid Fuzzy Neural Network
MAPE	-	Mean Absolute Percentage Error
MISO	-	Daily Report of Midwest Independent System Operator
MILP	-	Mixed Integer Linear Programming
MINLP	-	Mixed Integer Nonlinear Programming

LIST OF SYMBOLS

a	-	Operating hour
C^k	-	Tariff in Dollars in the time slot k
E_k	-	Power demand at time slot k
f_c	-	Electricity consumption function
i	-	Index of appliance to be scheduled
j	-	Index of number of load phases associated within appliances
k	-	Time slot
N	-	Number of appliances

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CHAPTER 1

INTRODUCTION

1.1 Background Study

The electric utilities play an important role in increasing its generation and transmission capabilities, to successfully achieve this demand, a lot of other parties should hand in hand aid and contribute with new technologies and better dogmas or policies [4]. The smart home system is later envisioned to ominously help with this demand response as it includes more distributed renewable sources with the usage of smart appliances [12].

Smart homes, or home automation began to increase in popularity in the early 2000s. Smart home in general is a home that contains a communication network that connects with appliances and also being controlled remotely by a smartphone or computer. Not only smart homes make life easier and convenient, but it would save energy and money too.

The sole problem of today's power generation and distribution system is the surge in energy demand during peak hours in residential area. The impact of higher peak load in a single home would increase higher generation of electricity on the supplier side. Hence, would increase the electricity bills. Companies around the world are forced to put in additional generating units to achieve this peak demand [12]. The rising of renewable energy into the system as surplus or additional energy also however would introduce mix generation hence making the system more complex and most importantly costly.

Therefore, smart home system is a necessary component of the smart power grid, which permits and allow active participation from residential end users in reducing this peak demand or levelling the load accordingly to reduce usage of appliance during peak hours. The changes from generation-follows-load to load-follows-generation has somewhat shaped a new improved dimension in the relationship of the utility and customer in the energy industry.

By scheduling the appliances of the smart home, the operation of these appliances can be shifted to off-peak hours and spread over a longer period of time that would in turn reduce the excessive energy consumed. Not only that, electricity bills would be reduced which would benefit the customer in return. Also, the user's preferences should also be considered when applying this appliances scheduling. Thus, optimizing this scheduling of appliances should greatly minimize the peak demand and electricity bills.

This thesis presents the method of day-ahead prediction of energy consumption of a smart home through Artificial Neural Network (ANN). A demand forecast of a 24 hours a day for various types of appliances would be generated through MATLAB by using yearly data from previous year of a smart home. This data would be injected in the system and undergo a training process through backpropagation method after going through data normalization. Normalizing the data would perfected the values with range between 0 and 1 that could increase the chances of correct predictions. The system then forecast the consumption of energy of a smart home for the next day and calculate the Mean Squared Error (MSE) of the system.

Hence, optimizing the usage of appliances would significantly impact the efficiency of a smart home [4]. It is presumed that by having a prediction of the energy demand of a smart home, consumers could understand energy saving better and contribute to a healthier and improved production and generation of energy. A large number of research have been made regarding optimal scheduling with various kind of methods hoping to advance and optimize scheduling of smart appliances. More studies are expected to be made in future in helping achieving the goal to reduce this high demand of electricity all around the world. Load scheduling for smart home could be one of the best ways to do so.

1.2 Problem Statements

Previous research has shown that load scheduling is one of the form of load management to brutally save energy and reduce electricity bills by minimizing demand. However, problem arise when it is not scheduled at optimum. Issues are such as:-

a) Prediction is based on estimation. Energy consumption of appliances in load profile are only estimated which has a possible high percentage of error making the load scheduling less accurate.

b) Insufficient data. While load scheduling is based on the data taken from house appliance of a single home, conventional way collects appliances that runs or turned on in the single smart home. This disrupts the efficiency of load scheduling.

c) Inconsistency of load consumption. Based on manual scheduling, load consumption data of these appliances is inconsistent. The time of the day of the year and the season of the month were not taken into consideration. Eventually reduces the precision of load scheduling.

Artificial Neural Network is then proposed for day-ahead prediction of energy consumption of appliances prior to load scheduling for a better and optimum output. Data input in ANN considers the time of the day, season and the weather [15]. Hence, using forecasting method in ANN can guarantee the optimization of load scheduling.

1.3 Research Objectives

In regards to the problem statement mentioned earlier, four objectives are being brought forward to solve these problems. Stated below are this project’s objectives:-

a) To analyse a yearly data of energy consumption of a smart home and study the load profile of each appliances.
b) To predict the next day energy consumption from a 1 year 1 hour resolution data of a single smart home in 2014 using Artificial Neural Network (ANN).

c) To assess the effectiveness and the accuracy of the prediction used for load scheduling through number of hidden layer size and number of trials.

d) To optimize load scheduling of the smart home using Mixed Integer Linear Programming (MILP) to reduce peak demand and electricity bill.

1.4 Significance of the Research

Such study is important to the society and people living in Malaysia to bring awareness in the benefits of scheduling appliances of their home. Scheduling home appliances at optimum predominantly reduce energy consume during peak hours and eventually reduced total load consumption and electricity bills.

1.5 Research Scope

To analyse a yearly data of energy consumption of a smart home and study the load profile of each appliances	• A yearly dataset of 5 appliances which are space heater, air conditioner, personal computer, dishwasher and water heater • Dataset extracted from a single smart home in Little Rock, Arkansas, U.S • The dataset consisting 8,760 data is normalized using standard function in Microsoft Excel
To predict the next day energy consumption from a 1 year 1 hour resolution data of a single smart home in 2014 using Artificial Neural Network (ANN)	• Load forecast is done through Artificial Neural Network (ANN) technique in MATLAB • Neural Fitting app is chosen for the train function of the model • Prediction is in a form of 24-hour classes • ANN building inputs consist of 14 attributes with an output of 5
To assess the effectiveness and the accuracy of the prediction used for load scheduling.	• Performance of ANN model is studied by the Mean Squared Error (MSE) • The output of proposed work is compared with different hidden layer size and number of trials
To optimize load scheduling of the smart home using Mixed Integer Linear Programming (MILP) to reduce peak demand and electricity bill	• Load scheduling is done using Mixed Integer Linear Programming (MILP) in MATLAB • Tariff price used is based on the Daily Report of Midwest Independent System Operator (MISO) from the Federal Energy Regulatory Commission (FERC)

1.6 Thesis Outline

There are 5 chapters in this report where the first chapter explains the introduction in great length containing background of the study, problem statements, research objectives, and significance of the research and research scope.

Chapter 2 on the other hand encompasses the few literature reviews related to the topic for both ANN and MILP. More detailed clarification and explanation on other methods used by other researches on these two fields. This topic also touch on the overview of the optimization method, the type of appliances, research gap and also the summary.

Following this chapter is where research methodology is enlightened further with proper flow. Chapter 3 provides understanding of the flow of methods used based on the objectives stated earlier which are the data acquisition of the appliances, the process of prediction of load consumption, objective function and constraints of load scheduling and the assessment and comparison of both before and after optimization.

Chapter 4 then discussed the results obtained from the work thoroughly that contains the forecasted day-ahead load consumption of the 5 appliances through ANN, the performance of the ANN prediction model and the comparison of load scheduled appliances before and after optimization.

Lastly, Chapter 5 clarifies the conclusion of the research done and the proposed recommendation of the work whereas Chapter 6 then covers the project management and project schedule of the entire thesis.

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