PREDICTING SYNTHETIC LOAD PROFILE USING ANFIS BASED ON ELECTRICITY USAGE BEHAVIOUR

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To my beloved parents, thank you.

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ABSTRACT

Predicting the energy consumption in a building is an effective technique for reducing energy demand and improving energy efficiency. Hence, a predictive tool is required to predict the energy consumption. In this study, proposed methodology adapted the adaptive neuro-fuzzy inference system (ANFIS) method to learn the patterns of electricity usage behaviour with the corresponding load profile. The proposed ANFIS was applied to the energy consumption pattern of university students at a residential college. The result showed that the developed method predicted the synthetic load profile accurately even when tested with unpredicted input datasets of electricity usage behaviour. This study showed that the MAPE and RMSE of the proposed ANFIS were 3.96% and 0.9204, respectively. In addition, the proposed ANFIS outperformed the state-of-the-art synthetic load profile prediction techniques of support-vector machine (SVM), multiple linear regression (MLR), Gaussian process regression (GPR), and fuzzy inference system (FIS). Finally, the effectiveness of various demand-side management (DSM) strategies was implemented at the residential college to validate the performance of the proposed ANFIS. In this study, the load-clipping strategy was better than other DSM techniques, as it saved more energy of up to 57%.

ABSTRAK

Meramalkan penggunaan tenaga dalam bangunan ialah teknik yang berkesan untuk mengurangkan permintaan tenaga dan meningkatkan kecekapan tenaga. Oleh itu, alat ramalan diperlukan untuk meramalkan penggunaan tenaga. Dalam kajian ini, pendekatan baru dalam meramalkan profil beban sintetik berdasarkan tingkah laku penggunaan elektrik. Metodologi yang dicadangkan mengadaptasi kaedah adaptive neuro-fuzzy inference system (ANFIS) untuk mempelajari corak tingkah laku penggunaan elektrik dengan profil beban yang sesuai. ANFIS yang dicadangkan digunakan untuk mempelajari corak penggunaan tenaga elektrik oleh pelajar universiti di kolej kediaman. Hasilnya menunjukkan bahawa kaedah yang dibentangkan dapat meramalkan profil beban sintetik, dengan tepat walaupun diuji dengan set data input yang tidak dapat diramalkan mengenai tingkah laku penggunaan elektrik. Kajian ini menunjukkan bahawa MAPE dan RMSE dari ANFIS yang dicadangkan masing-masing adalah 3.96% dan 0.9204. Selain itu, ANFIS yang dicadangkan mengatasi teknik ramalan profil beban sintetik yang lain seperti support-vector machine (SVM), multiple linear regression (MLR), Gaussian process regression (GPR), dan fuzzy inference system (FIS). Akhirnya, keberkesanan pelbagai strategi pengurusan permintaan (DSM) dilaksanakan di kolej kediaman untuk mengesahkan prestasi ANFIS yang dicadangkan. Dalam kajian ini, pemotongan beban lebih baik daripada teknik DSM lain kerana dapat menjimatkan lebih banyak tenaga sehingga 3.852 MW.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANFIS	–	Adaptive neuro-fuzzy inference system
AI	–	Artificial intelligence
ANN	–	Artificial neural network
CCTV	–	Closed-circuit television
C-SCADA	–	Cloud-based supervisory control and data acquisition
DR	–	Demand response
DSM	–	Demand-side management
DSO	–	Direct search optimisation
DT	–	Decision tree
ECC	–	Energy-consumption controller
FCM	–	Fuzzy C-mean clustering
FIS	–	Fuzzy inference system
GD	–	Gradient descent
GP	–	Gaussian process
GPR	–	Gaussian process regression
HMM	–	Hierarchical multi-matrices
KNN	–	k-nearest neighbour
LED	–	Light-emitting diode
LR	–	Linear regression
LSE	–	Least square estimation
LSSVM	–	Least-square support-vector machine
MAE	–	Mean absolute error
MAPE	–	Mean absolute percentage error
ML	–	Machine learning
OP-ELM		Optimally pruned extreme learning machine
RCGA	–	Real-coded genetic algorithm
RMSE	–	Root mean squared error

STLF	–	Short-term load forecasting
SVM	–	Support-vector machine
SVR	–	Support-vector regression
UTHM	–	Universiti Tun Hussein Onn Malaysia
P_{peak}	–	Peak power
$P_{reduction}$	–	Power reduction
E_{saving}	–	Saving energy
E_{total}	–	Total energy
μ	–	Membership function
O_i^1	–	Output of Layer 1
O_i^2	–	Output of Layer 2
O_i^3	–	Output of Layer 3
O_i^4	–	Output of Layer 4
O_i^5	–	Output of Layer 5
w_n	–	Firing strength
$\overline{w}_n$	–	Output of normalisation layer
f_n	–	Linear of consequent parameter
L_i	–	Consequent parameter
α_j , γ_j	–	Antecedent parameter
L_m	–	Number of load inputs
ξ_i	–	Slack variable
ε	–	Deviation
α_o	–	Coefficient
β_o	–	Coefficient
σ^2	–	Variance
β_i	–	Change in energy consumption
X_i	–	Level of usage of electrical appliance
P_i^t	–	Historical data
y_t	–	Output variable
x_t	–	Input vector
Ʈ	–	Training dataset
τ^2, ω, α	–	Predicted hyper-parameters
K	–	Exponential kernel

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CHAPTER 1

INTRODUCTION

1.1 Background of study

In realising Industrial Revolution 4.0 (IR4.0), the digital twin concept is one of the most promising and crucial technology enablers which connects the physical and virtual realms by focusing on the rapid development of simulation, data acquisition, data communication, and other advanced technologies seamlessly [1]. An example of the implementation of the concept in power system operation is shown in Figure 1.1 The figure illustrates that the real-time measurement of the actual power system is continuously fed to its digital twin in virtual space [2]. Any required operational modifications can be applied first in the digital twin of the physical grid to predict operational insight before changes are implemented in the real system.

Consequently, implementing the digital twin concept is beneficial in power system applications that directly depends on stochastic human behaviour, such as in the demand-side management (DSM) application. DSM is utilised in the power system to modify the load profile by influencing the end-user electrical utilisation behaviour [3]. In the literature, several strategies are reported to realise this technique. However, the effectiveness of each strategy depends on a myriad of factors (e.g., ambient temperature, daily activities, or cost), and implementing each technique may require a considerable capital investment and person-hour [4]. Hence, the implementation of the digital twin concept in the demand-side management application is required to evaluate the performance of DSM on the actual real-time system. A predictive tool to predict the resulting synthetic load profile following the implementation of the DSM strategy is required to ensure its effectiveness on the targeted user before implementing it in practice.

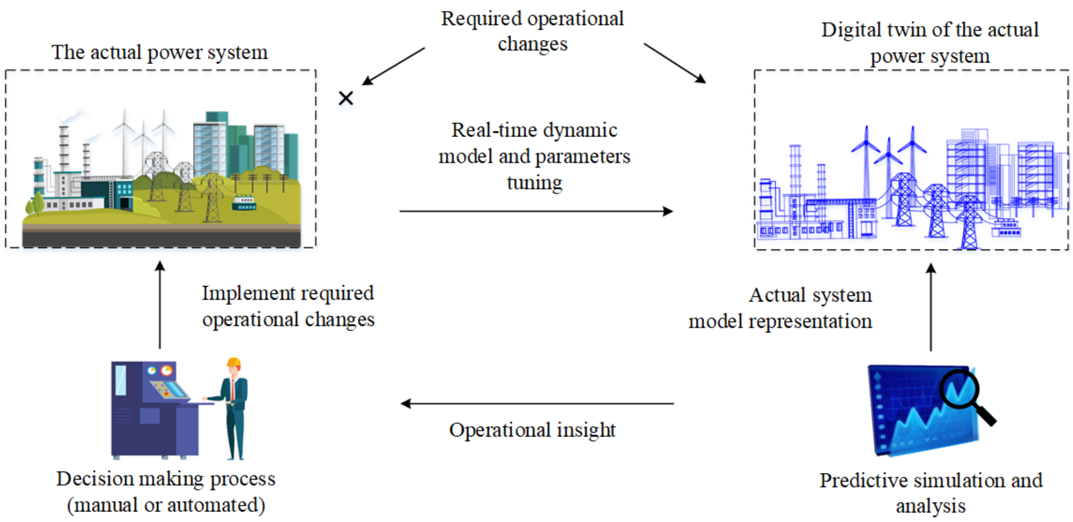

Figure 1.1: Electrical digital twin.

In the literature, there are several works reported to address the need for the predictive tool. The methods are data-driven and can be classified into two categories: mathematical-model-based and machine-learning-based methods. The researchers in [5] and [6] reported mathematical modelling to predict the synthetic load profile. The utilisation pattern of the load with the corresponding load profile using a bottom-up mathematical modelling approach was presented. In [7]–[10], the researchers proposed machine-learning-based methods to predict the load profile based on energy signatures. Examples of machine learning used by the researchers are ANFIS, MLR, SVM, and GPR. In addition, the employed machine-learning-based methods considered the energy pattern, such as energy consumption pattern, energy consumption's rate of change, temperature, and humidity, to predict the synthetic load profile.

In this study, the ANFIS method was utilised to capture the dynamics of electricity usage behaviour to predict the synthetic load profile. Similarly, the application of ANFIS has been widely reported in the literature to address various data prediction challenges in power system studies [10]. The study used a data-driven machine-learning method which is it does not require an extensive mathematical modelling process. Thus, this study utilised the energy consumption pattern of students residing at the Tun Dr. Ismail Residential College (TDIRC) at Universiti Tun Hussein Onn Malaysia (UTHM) to develop the training dataset for the ANFIS. The method modelled the electricity usage behaviour of the students and associated it with the corresponding load profile in the training dataset development. The types of users considered in this study possessed a unique challenge in the DSM strategy. The students are not directly responsible for the electricity bill because it is included in the accommodation fees. In addition, the students are the most dominant electricity consumer in a university. Thus, the university management may need to apply DSM applications to reduce and manage the energy consumption of the students.

1.2 Problem statement

Predicting the energy consumption in a building is an effective technique for reducing energy demand and improving energy efficiency. For example, university campuses represent specific groups of various buildings with substantial energy consumption. A residential college represents the most energy usage among university buildings. Moreover, the number of students reflects the energy consumption of the residential college. Hence, it is necessary to gather information on electricity usage behaviour to predict the synthetic load profile. Most reported studies measured the energy of electrical appliances to characterise and recognise the appliances' behaviour to predict the energy load profile [11], [12]. However, installing smart sockets involves an enormous cost to monitor the behaviour of each appliance.

Moreover, it is a challenging task to predict energy consumption accurately. A machine-learning method is well adapted to the electrical load's nature, as it can model complicated nonlinear connections through a learning process containing historical data patterns. Various ML methods have been used widely to predict energy consumption [13]–[15]. However, it remains questionable how to incorporate the relationship between the reference buildings' identification and predict energy consumption using substantially fewer building data to reduce the complexity of prediction models.

Additionally, an essential method is needed to manage energy demand, as it always fluctuates dramatically during short time frames. DSM is a powerful tool that adjusts the supply by increasing or decreasing the generation or adding/curtailing additional resources to meet the demand. DSM techniques to reduce the load profile's peak and the need for facility investment have been reported in the literature. Nevertheless, most of the reported techniques are based on price manipulation to control the users in utilising their load [16]–[18]. Therefore, these techniques are not suitable for students who are paying electricity bills directly. The electricity bill is included in the residential college fees, where the residents are able to use electricity without any limit. Hence, it is necessary to come out with a DSM technique that is able to manage the energy demand of this type of electrical user.

1.3 Hypothesis

The modelling of electricity usage behaviour depends on the number of users, the users' schedule and activities, and the type of load. Usage behaviour varies according to the time of day. If the electricity usage behaviour aligns with the actual load profile, then the ANFIS can predict the synthetic load profile accurately.

1.4 Aim

This study aimed to propose a novel approach for predicting a synthetic load profile based on electricity usage behaviour by using the ANFIS method for DSM applications.

1.5 Objectives

This research work embarked on the following objectives:

a) To study the relationship between electricity usage behaviour and electrical appliance usage of university students in UTHM,

b) To develop a novel synthetic load profile predictor based on electricity usage behaviour,

c) To evaluate the performance of DSM strategies using the synthetic load profile predictor.

1.6 Scope of study

The scope of the research is as follows:

a) The study was conducted at the Tun Dr. Ismail Residential College (TDIRC) at Universiti Tun Hussein Onn Malaysia (UTHM).

b) Analysis and simulation works were conducted using MATLAB software.

c) The data collection represented the load consumption in each hour for an entire day. It was repeated for 12 months in year 2018.

d) The synthetic load profile was modelled by using the ANFIS method.

e) The performance of the proposed method was compared with those of other methods, such as SVM, MLR, GPR, and FIS.

f) The study considered only three DSM techniques, which were load clipping, load shifting, and load conservation.

1.7 Research contribution

This dissertation showed the synthetic load profile prediction performance based on electricity usage behaviour using the ANFIS method. This thesis introduced a method to predict the synthetic load profile based on the electricity usage behaviour of students at a residential college. A prediction method to predict the synthetic load profile is the foundation of this thesis. In this study, the electricity usage behaviour of the students at a residential college and the associated load profile were captured to develop the prediction tool conducted in the ANFIS.

The proposed ANFIS outperformed the state-of-the-art modelling synthetic load profile prediction techniques, such as SVM, MLR, GPR, and FIS. The result demonstrated that the proposed ANFIS can accurately predict the synthetic load profile based on electricity usage behaviour compared to other AI techniques. Also, the effectiveness of the proposed method was evaluated by applying the DSM techniques to the synthetic load profile. In this study, the application of DSM techniques may be advantages to the university management as it can save the energy up to 25.6%. Moreover, the proposed ANFIS and DSM method not just applicable for this case study building but it is also can be applied to other building that does not charge the electricity bills to the users such (e.g., residential of factory workers)

1.8 Outline of thesis

This thesis is organised into five chapters. Following this introductory chapter, the remaining chapters are described briefly as follows:

Chapter 2 presents the related background of AI approaches for load consumption prediction. The current status, prospect, possible challenges, and solutions are briefly discussed in this chapter. Moreover, in this chapter, demand-side management in power system applications was also discussed. The various purposes of this approach are concisely discussed in this chapter.

Chapter 3 presents in-depth the proposed research methodology used in this work to reach the objectives. The processing of the actual data, the mapping of electricity usage behaviour, the development of the adaptive neuro-fuzzy inference system (ANFIS), and the comparison of different AI techniques are elaborated thoroughly in this chapter. The flow of the project methodology is presented in a diagram for readers' convenience.

Chapter 4 presents the application, results, and discussion of the proposed methodology. Moreover, the performances of the proposed method were compared with various machine-learning algorithms to demonstrate the superiority of the technique. Then, the application of the proposed method is demonstrated to evaluate the effectiveness of various DSM strategies before implementing them in practice.

Chapter 5 presents the summary of the main contributions and limitations of this study and provides some insights from this research for future studies.

CHAPTER 2

LITERATURE REVIEW

This chapter highlights the boundary of the work with the state-of-the-art techniques presented in this thesis. In this chapter, the works reported in the literature on load profile modelling of electricity usage are reviewed. Besides that, the utilisation of AI methods to predict load consumption is discussed in this chapter. Then, the research gap that sets the motivation of this research was identified. Finally, the DSM strategies are presented to evaluate the effectiveness of the methods' performances in managing a building's energy consumption.

In this chapter, the methods of load profile modelling based on different electricity usage behaviours are reviewed in Section 2.2. Next, the AI approaches to predict the load profile based on electricity usage behaviour are discussed in Section 2.3. There are five methods discussed in this section: ANFIS, SVM, MLR, GPR, and FIS. The literature review of these different techniques to predict load profile is explained in Subsection 2.3.1 until 2.3.8. Lastly, in Section 2.4, DSM applications in practice were reviewed.

2.2 Load profile modelling

Synthesising the load profile is critical in exploring future demand response and load curtailment prospects for smart grid implementation. Synthesising the load profile will vary according to the customer type (residential, commercial, and industrial), temperature, and holiday season. There are various methods reported to reduce the need for data acquisition and improve accuracy in representing usage behaviour in the load profile. In recent years, various researchers widely used bottom-up and top-down approaches to model the electricity load profile as shown in Figure 2.1. Most researchers utilised in their works the load profile modelling of residential houses or buildings. The comparison of previous works is shown in subsection 2.2.4.

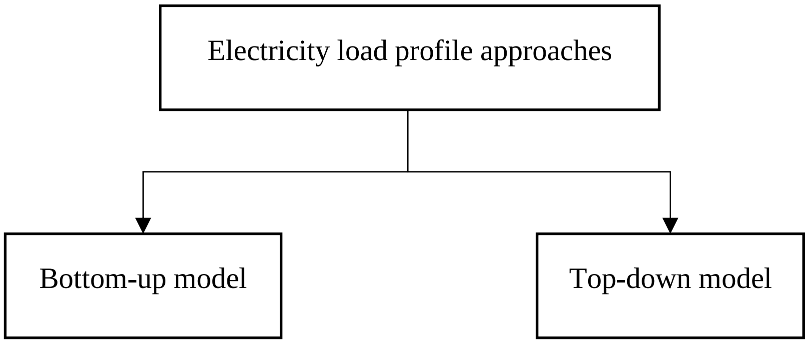

Figure 2.1: Electricity load profile approaches

2.2.1 Approaches in load profile modelling

A classification system identifies vital characteristics, such as technique, sampling rate, application, and statistical data [19], to create a residential load profile model in the method. Currently, there are two types of residential load profile models: bottom-up and top-down models. For instance, a model is assigned to the bottom-up model subgroup if the electricity consumption of various devices in a household is utilised to compute the household's electricity consumption. In contrast, the model is assigned to the top-down subgroup when macro-economic parameters are used to calculate the household's electricity consumption.

The sampling rate describes the model's ability to provide the most refined grain output. The output is chosen rather than input because models might have numerous inputs with multiple sampling rates, and outputs usually have a single sampling rate [20]. Hence, an hourly sampling rate is used for a model that takes quarter-hourly occupancy profiles as input to compute a household's hourly electricity usage. However, the sampling rate is categorised as quarter-hourly if quarter-hourly occupancy profiles are used to assess a household's quarter-hourly electricity usage.

Furthermore, a model's primary intended application is described by the application. In general, the DSM subcategory will be ascribed to the model used in DSM. Hence, the planning and control design model of energy systems and distribution grid is assigned to the subcategory of planning and control design of energy systems and distribution grids. A residential load profile subcategory is assigned when the model aims to estimate the power consumption of a single house or a group of houses.

Finally, the statistical technique defines the main statistical approach utilised to predict the residential load profile. If the Markov chain technique is the central statistical technique employed in a model, the model is placed in the Markov chain subgroup. If a Monte Carlo technique is applied, and the model is assigned to the Monte Carlo subgroup [21].

2.2.2 Bottom-up model

Bottom-up residential load profile models calculate the individual dwelling energy or electricity consumption and extrapolate the results over a target area or region [20]. This model is developed by identifying the electricity consumption of each appliance in a household, the behaviour pattern of the household occupants, and electrical appliance usage, and then combining the information to produce the total household load profile. In addition, the house's characteristics, weather conditions, and heating/cooling might be included to determine the intensity of electrical appliance usage. This model can generate comprehensive details of single-household electricity load profiles, which can be adjusted to include or exclude appliances, include different device usage patterns, and include forthcoming technologies. An individual household's influence on the load profile of a residential block is suitable for simulation investigation of the effect of different technologies, policy decisions, or energy optimisation methods. Furthermore, the information also can be used for load prediction at the utility level.

In addition, most of the reported studies utilised the American Time Use Survey to gather information on usage behaviour to model the load profile [22], [23]. The ATUS is administered using computer-assisted telephone interviews rather than paper diaries, as in many other countries [24]. Moreover, the ATUS measures the amount of time people spend doing various activities, such as paid work, childcare, volunteering, and socialising. The researchers in [25] also reported a similar method for gathering this information. A comprehensive student activity survey form developed based on typical activities was discussed in [26].

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APPENDIX B

LIST OF PUBLICATIONS

1. **Omar, N.**, Ariff, M. A. M., Mohd Shah, A. F. I. and Mustaza, M. S. A. Estimating synthetic load profile based on student behavior using fuzzy inference system for demand side management application. Turkish Journal of Electrical Engineering & Computer Sciences. 2020. 28(6): 3193-3207.
   [Q3 – Web of Science]

2. Mohd Shah, A. F. I., Ariff, M. A. M., **Omar, N.**, and Mustaza, M. S. A. A new intelligent time-series prediction technique for coherency identification performance enhancement. Kuwait Journal of Science. 2020. 48(4).
   [Q2 – Web of Science]

APPENDIX C

VITA

The author was born on March 13, 1995, in Kluang, Johor, Malaysia. She went to Kluang High School for secondary education. She pursued her diploma of Electrical Engineering in Universiti Tun Hussein Onn Malaysia (UTHM) in 2013. She then enrolled B.Eng. (Hons) in Electrical Engineering in 2019. Upon receiving her bachelor's degree, she continued her study in Master of Electrical Engineering in 2019. During her study, she was appointed as Graduate Research Assistant (GRA) of Power System under Faculty of Electrical and Electronic Engineering (FKEE). Besides, she is currently a member of the Institute of Electrical and Electronics Engineering (IEEE). In addition, she co-authored a paper published in the Turkish Journal of Electrical Engineering and Computer Science journal, which is indexed with the Web of Science.