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Estimating synthetic load profile based on student behavior using fuzzy inference system for demand side management application

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Abstract: This paper proposes a novel approach of estimating synthetic load profiles based on the electrical usage behavior using the fuzzy inference system (FIS) for demand side management (DSM). In practice, DSM is utilized to change the pattern of electrical energy consumed by end-users to modify the load profile by manipulating the price of the electricity. This study focuses on the energy consumption consumed by students who are paying electricity bills indirectly. Therefore, the effectiveness of conventional DSM methods on this user requires further investigation. In this study, the FIS estimates the synthetic load profile based on the student's behavior profile. Then, three DSM techniques: load clipping, load shifting, and load conservation, are applied to the electrical usage behavior model. The FIS estimates the synthetic load profile based on the modified electrical usage behavior model with these DSM techniques. From this estimation, the synthetic load profiles are analyzed and compared to evaluate the effectiveness of the DSM methods on the students. The result shows that the FIS estimates the synthetic load profile satisfactorily. Also, load conservation is the most effective technique in reducing the peak load profile and power consumption for this type of user. Conclusively, the result implies that the proposed methodology can be used to evaluate the effectiveness of the DSM method to reshape the load profile.

Key words: Synthetic load profile, demand side management, fuzzy inference system, digital twin, smart grid

1. Introduction

In the industrial revolution 4.0, the real-time analytic unlocks performance enhancement and efficiency improvement of the system in real-time. The analytic engine can take the form of a digital twin of the real networked system. In power system operation, the digital twin concept is the key to the advancement of the smart grid system. The concept is referred to as a virtual mirror of the real power system that represents its state and behavior [1]. Various power system operations may benefit from this concept, especially for demand side management applications. The effectiveness of the demand side management varies with time, operation, and type of user [2]. The demand side management modifies the load profile pattern by changing the user behavior in consuming the load [3]. Thus, the digital twin may hold the key to validate the effectiveness of numerous DSM techniques for its suitability towards this variation. To realize the digital twin concept in DSM application, a tool to estimate the synthetic load profile is needed to verify the effectiveness of any DSM technique.

This project proposes a tool to estimate the synthetic load profile estimator based on the electrical user behavior model. The method works as an assessment tool to evaluate the effectiveness of the DSM applications

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on the load. In the literature, the reported DSM technique is based on price manipulation to control users in utilizing their load [4]. However, not all types of users can be manipulated through the tariff. The college student, factory worker, and industrial worker are the type of users that are not directly responsible for the electricity bill. This situation addresses a challenge to the facilities administrator to manage electrical load usage. In this study, college students are chosen as the subject as they are the dominant electrical users in a university. The electricity bills utilized by the college student are usually incorporated into their accommodation fees. In other words, the student pays electricity bills indirectly. Thus, the university management needs to minimize the energy consumption and electricity bill of the residential college. For example, according to Malaysia Efficient Management of Electrical Energy Regulation 2008 [5], all installation that utilized 3,000,000 kWh from the national grid for six consecutive months is required to come out with an energy management objective and plan for the installation. Therefore, the proposed technique may serve as an analytical tool to evaluate the effectiveness of various DSM techniques within the compound. The synthetic load profile estimator utilizes FIS to capture the dynamics of the electrical usage behavior of the residential college students to estimate the corresponding load profile. The electrical user behavior is modeled based on the student's daily activities, number of students, and the typical types of load that is generally used by students. The application of DSM techniques modifies the electrical usage behavior model. Consequently, the proposed method estimates the corresponding load profile based on the modified behavior model. The load profiles based on the variation of the DSM technique are compared to evaluate their effectiveness on this type of user.

Following this introduction, this paper is organized as follows: Section 2 describes the state-of-the-art of the synthetic load profile estimator. Then, the development of the synthetic load profile estimator is elaborated in Section 3. Next, Section 4 presents the application of the proposed method on the actual load profile data to validate its estimation accuracy. Consequently,the effectiveness of the proposed method on various DSM techniques is discussed in Section 5. Finally, Section 6 concludes this study.

2. State-of-the-art

Synthesizing load profile is critical in exploring the future demand response and load curtailment prospect for the smart grid implementation. There are various methods reported to reduce the needs for data acquisition and to improve the accuracy in representing the user behavior in the load profile. The researchers in [6] utilize the stochastic model to investigate the factor that influences the energy consumption of the domestic sector. The study focuses on the effects of occupant behavior, appliance stock, and efficiency on the load profile behavior of a user. The method incorporates the usage of the appliance into a probability distribution. Although the method can synthesize the load profile of a single user accurately, other factors that may cause the deviation in the estimation, such as an extreme seasonal event and thermal electric heat generation, are not considered in the study. In [7], the researchers establish a mathematical model to represent the load profile of each type of load based on the bottom-up model. The report shows that the method can synthesize the load profile with the details on the electrical appliances, its energy requirement, and the consumption pattern. However, various critical factors are considered in the development of this method, such as abnormal weather, annual events, and public holidays. On the other hand, the technique reported in [8] synthesizes the residential load profiles using the behavior simulation method. This method synthesizes the residential load profile by considering the user behavior of different career backgrounds. However, the method requires detailed household information such as the information of family members, living habits, home appliances, and others as its input to synthesize the user load profile accurately. Next, a bottom-up method to estimate the household load profile based on resident consumption behavior is reported in [9]. The technique synthesizes the load profile by using the extraction model formulated based on the comparison between the external environmental factors and household factors. Consequently, the reported bottom-up method can estimate the load profile of different family categories accurately. Besides, the result shows that the method can synthesize the load profile behavior of the commercial users or highly localized power grid as well.

Based on the literature review, the development of the methods to synthesize the load profile is focused on the standard household electrical usage behavior. To this author's knowledge, the load profile behavior of the student has not been investigated yet. The influence of the student behavior on the overall load profile is significant because the load consumption in the university varies according to the academic calendar. The electricity bills associated with the load profile of students are incorporated with the accommodation fees. Therefore, any DSM method that manipulates the tariff of electricity to control the load is no necessary suitable. Consequently, the development of a method to synthesize the load profile based on the electrical usage behavior of various types of users is required.

3. Estimating synthetic load profile using FIS

Figure 1 shows the load profile modeling utilized in this project. From the figure, the load profile modeling is segregated into three vital components: modeling of consumer electrical usage behavior, the development of FIS, and estimating the corresponding load profile. The modeling of electrical usage behavior requires the number of students, activities, and appliances which reflect the trends of energy consumption of the user. Consequently, the FIS is utilized to capture and represent the energy consumption trend from the data and to estimate the synthetic load profile based on student behavior. For FIS to effectively capture the trend from the data, a comprehensive input-output pair is needed to develop the if-then rules of the FIS. The development process will be discussed in the following subsection.

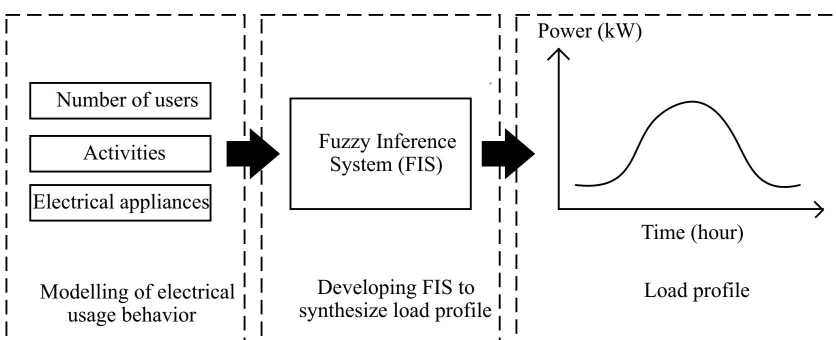

Figure 1. The block diagram of estimating synthetic load profile.

3.1. Modeling of electrical usage behavior

Figure 2 shows the information considered to model electrical usage behavior. In this study, the number of users, the user's daily activities and schedules, and the types of electrical appliances are used to represent the user's electrical usage behavior. Several methods are required to obtain this information. For example, the number of users is obtained from the user's registration record. However, the other two information is not available in any official record. The activities and schedules represent the duration and frequency of appliances usage [10]. For example, as students go to their class in the morning, they will switch off the light and fan in their room. However, some of the students will only go to their class in the afternoon, and the other may not have class in the afternoon. Therefore, the variety of student activities and schedules should be captured to represent the electrical usage behavior accurately. On the other hand, the type of appliances is also crucial information to model the electrical usage behavior as it dictates the amount of power utilized by the user. The essential appliances such as light and fan can be known from the record. However, personal appliances may vary from one student to another. An ideal option to obtain this information is by monitoring the power consumption of each appliance directly. Smart sockets can collect and upload energy consumption information from each appliance to the data center with Wi-Fi communication [11]. Although this method may provide a viable solution to obtain this information, it requires an enormous cost to install this socket at each electrical power plug. Another option is by using cameras to monitor the user's activities as conducted in [12], but it may cause various privacy issues in the institution. In this study, an extensive survey is conducted to identify the number of uncontrollable loads and activities of students. An online survey is disseminated among the residential student and collected to model the electrical usage behavior of the student. A similar approach has been used to capture the student activities and schedule for other studies [13].

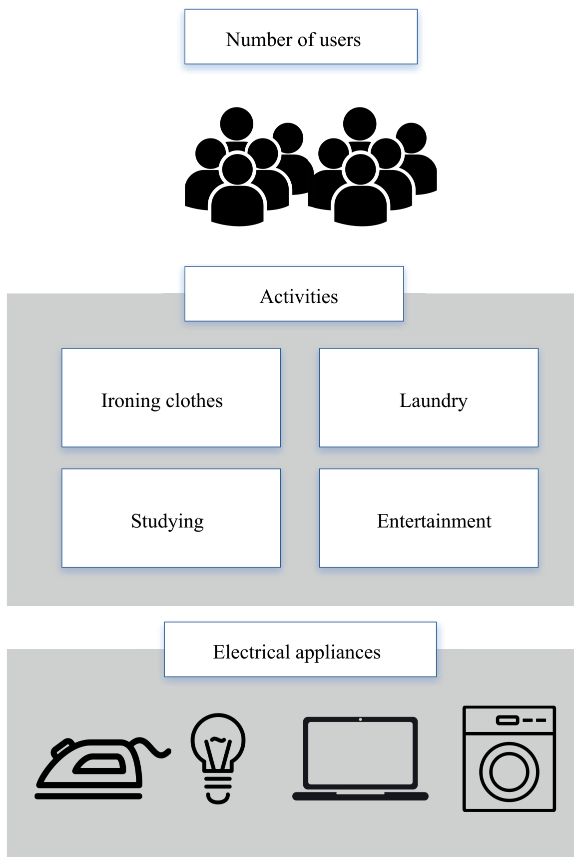

Figure 2. The modelling of electrical usage behavior.

3.2. Developing FIS to synthesize load profile

The development of FIS to synthesize the load profile is shown in Figure 3. Based on the figure, the FIS development is divided into two major parts: the formation of the input-output pairs and the development of

FIS itself. The input-output pairs are formed to develop the if-then rules for the FIS operation. It is worth noting that the FIS does not require any training phase [14]. In this paper, the load behavior model is set to be the input of the FIS. The utilization of the lamps, the ceiling fans, the exhaust fan, the hairdryer, the water heater, the washing machine, the iron, the laptop charger, the phone charger, and the table fan are arranged accordingly as the input. Consequently, the desired load profile obtained from the measurement of the incoming distribution board supplying electricity to the residential college is set as the output.

For the development of the FIS, there is two variant of FIS: Mamdani and Sugeno [15, 16]. In this study, Mamdani FIS is preferred because the system is intuitive, and it has widespread acceptance and well-suited to human input [17]. Figure 4 represents the basic principle of the Mamdani FIS. From the figure, the system consists of five different processes: fuzzification, fuzzy operation, implication method, aggregation method, and defuzzification to provide the desired output response corresponds to a given set of input.

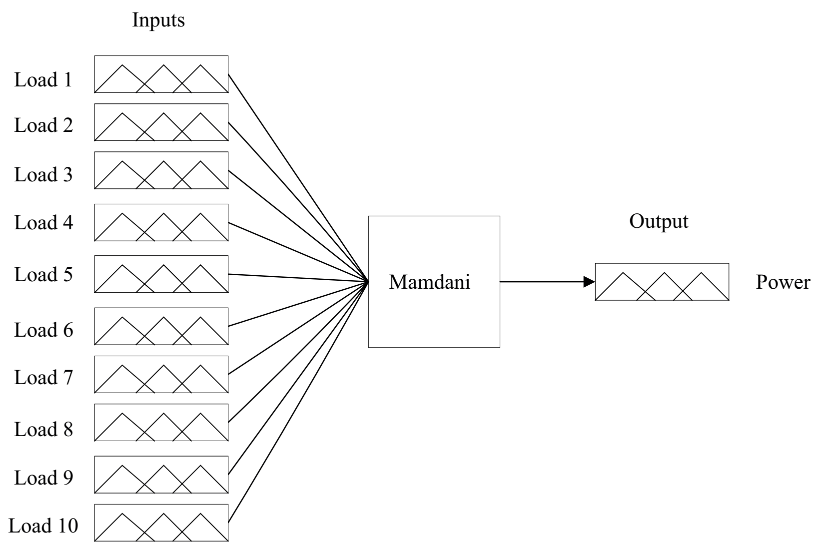

Figure 3. The development of FIS.

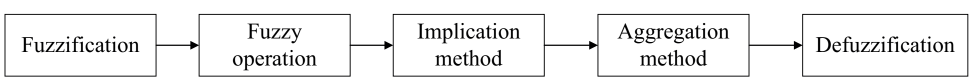

Figure 4. The basic operation of Mamdani FIS.

First, the inputs must be fuzzified according to the fuzzy linguistic set. In this study, the input of the FIS is the load usage model based on student activities. Therefore, the fuzzification process yields and classifies the input to the appropriate fuzzy sets that are represented by the membership functions. Figure 5 shows a sample of the membership function utilized in this study. From the figure, the membership functions are divided into three categories: low, medium, and high. These categories represent the frequency of electrical appliances' usage, respectively. The output from this process is the degree of the fuzzy set with the interval between 0 to 1. Consequently, the output of the fuzzification process is applied to the fuzzy operation process.

Following the fuzzification process, there will be a situation that the fuzzified input does not clearly belong to any fuzzy sets. As a result, the fuzzified input of a given fuzzy set has more than one part. The fuzzy operation is applied to address this issue by obtaining the number that represents the result of the fuzzified input for the given fuzzy set. Consequently, the number is employed on the output function. In other words,

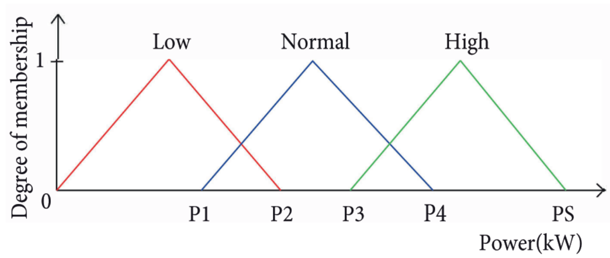

Figure 5. A sample of the membership function.

the fuzzy operation clarifies the fuzzified input with two or more fuzzy set membership values into one single truth value.

Next, the implication method is implemented to produce a corresponding consequent for a given fuzzified input. A consequent is a fuzzy set exemplified by a membership function, which is reshaped in this process using the function that is associated with the fuzzified input. The consequent is established based on the if-then rules developed using the input-output pairs. There are two typical implication methods to reshape the consequent: the AND, and PROD methods [18]. The AND method truncates the fuzzy set, while the PROD method scales the fuzzy set. In this study, the AND method is considered because it is less complex and easier to defuzzify later [19]. An example of the FIS rules utilized in this study is shown as follows:

Example 1 *If (Load$_1$ is Normal) and (Load$_2$ is High) and (Load$_3$ is High) and (Load$_4$ is Low) and (Load$_5$ is Low) and (Load$_6$ is Low) and (Load$_7$ is Normal) and (Load$_8$ is Normal) and (Load$_9$ is Normal) and (Load$_1$0 is High), then (Power is 1).*

The outcome of the implication method is a set of individual reshaped fuzzy set based on the corresponding fuzzified input. The reshaped fuzzy set must be combined in order to yield a decision. Aggregation method combines the fuzzy sets that represent the outputs of each rule into a single fuzzy set. The method is commutative, and there are three typical options to aggregate the fuzzy set: the maximum, probabilistic, and sum method [20]. In this study, the maximum method is considered because it is widely considered in the literature due to its simplicity [21].

The aggregated fuzzy set encompasses a range of output values. Thus, it must be defuzzified to resolve a single output value from the fuzzy set. There are several standard options to realize this process: the centroid, bisector, middle of maximum, largest of maximum, and smallest of the maximum [22]. This study considers the centroid method to defuzzify the aggregated fuzzy set by calculating the center of gravity of the area under the curve. The defuzzified fuzzy set represents the synthetic load profile estimated in this study.

4. Application, analysis and discussions

In this section, the proposed method is applied to the actual load profile data measured at the incoming distribution board of the student residential college. The load profile of Tun Dr. Ismail Residential College in Universiti Tun Hussein Onn Malaysia is considered in this study. The load consumption in 2017 is measured daily for the entire year. The electrical user behavior is modeled based on the number of students, daily activities, and the types of load used by the students. This information is gathered through online surveys of the student activities and the official student record. The FIS is developed using MATLAB software to estimate the synthetic load profile based on the electrical user behavior model of residential college students.

Consequently, the synthetic and the actual load profile is compared to validate the FIS performance in estimating the synthetic load profile based on the electrical user behavior model of the student.

Figure 6 shows the actual load profile of Tun Dr. Ismail Residential College in Universiti Tun Hussein Onn Malaysia (UTHM) in 2017. The measured data represents the average hourly load consumption by month. Each month is differentiated by colors and shapes. The load profile with the triangle, circle, and square shape represents the load consumption during semester 1, semester 2, and semester break, respectively. From the figure, it shows that the average hourly load consumption every month has a similar time trend of usage behavior. The load consumption reduces starting from 7 am until 6 pm, then increases back from 7 pm to 6 am. Besides, the load in May and June shows significantly higher consumption as compared to other months. On the other hand, the lowest load consumption is in July and August. As explained in Section 3, the actual load profile in Figure 6 is used to form the input-output pairs to develop the if-then rules for the proposed FIS.

Figure 7 illustrates the timeline of the student's daily activities and schedule in a day. The timeline is constructed based on the typical student activities. It is classified into 4 different periods: Stage 1, Stage 2, Stage 3, and Stage 4. Each period represents the combination of various activities in 6 hours, such as studying, entertainment, laundry, ironing, attending class, and outdoor activities. From the timeline, Stages 1 and 4 show a higher load consumption level as compared to Stages 2 and 3. The electricity usage decreases during Stages 2 and 3 because students conducted their activities outside the residential college area.

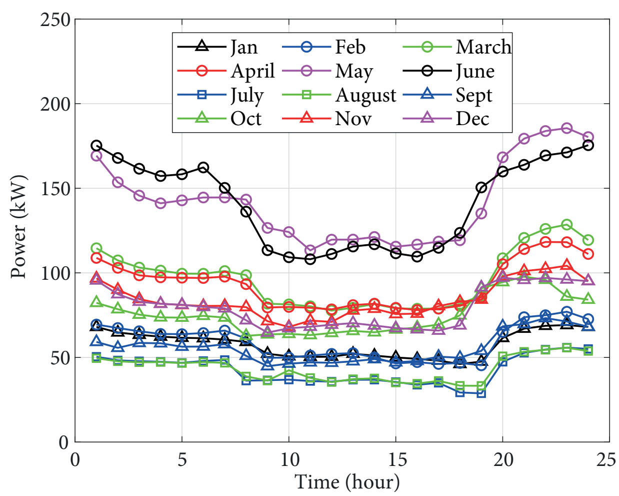

Figure 6. Actual load profile of Tun Dr. Ismail Residential College in 2017.

Table 1 shows the detail of the utilization of electrical appliances used in this study. The table tabulates the types of load, the corresponding power consumed, and the number of loads that are being used by the students. This data is collected from the residential college registration record of electrical appliances. From the table, there are ten types of connected loads which are the lamp, fan, exhaust fan, hairdryer, kettle, washing machine, iron, laptop charger, phone charger, and table fan. The highest power rating is the hairdryer and kettle due to the heating element inside the appliance. Meanwhile, the lamp and phone charger have the lowest power rating as compared to others. The total energy consumption depends on the power rating the numbers of load and the frequency of usage, which measured from the incoming power supply. In this college, there is no air conditioner or heater required as the geographical location of the college is close to the equator. Therefore, the resident does not require such appliances to deal with any extreme weather conditions. In this study, the

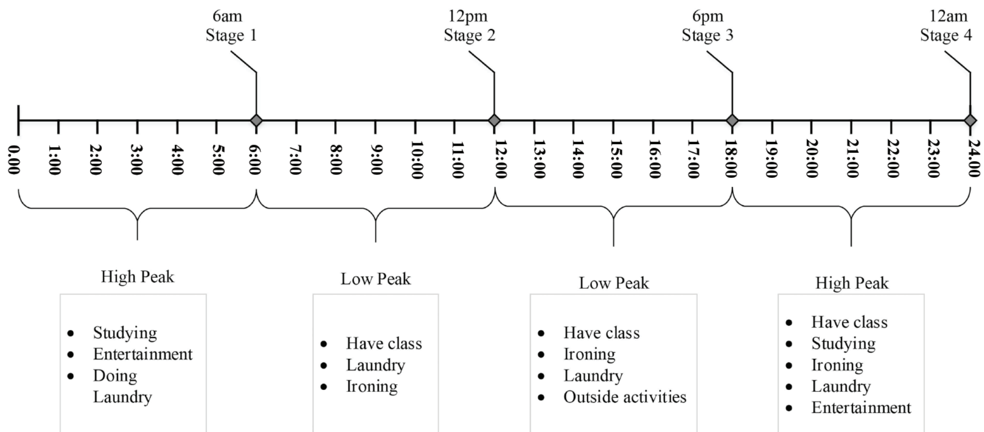

Figure 7. The timeline of student behavior.

utilization of electrical appliances is sampled hourly based on student activities. The appliances on/off status are based on the student activities which are translated into the load profile. In this study, the utilization of electrical appliances is sampled hourly. It is sampled based on the time interval used to model the electrical user behavior, which is sampled hourly as well. It is challenging to track the student within the university in greater detail as they are stochastic in nature. On the other hand, the energy consumption of electrical appliances is measured at the incoming power supply, and the appliances on and off status are modeled based on the student activities.

The timeline in Figure 7 is translated to the electrical usage behavior. Table 2 represents the electrical usage behavior during the active calendar years when the students are available in the residential college. In the table, the electrical usage behavior represents the load used by the student daily in March 2017. This month is considered in this study because it is the peak month of semester 2, where the student activities are the highest as compared to other months. The electrical usage behavior is applied to the FIS to estimate the synthetic average hourly load consumption in a month. This assumption is considered based on the monthly billing cycle of the organization. The table consists of ten types of electrical appliances that are used in daily activities, as listed in Table 1. The load usage of each electrical appliances is represented into three different conditions: low (L), normal (N), and high (H) signify 20%, 50%, and 100% of load consumption, respectively. The electrical usage behavior is applied to the FIS for the synthetic load profile estimation.

Figure 8 compares the actual and the synthetic load profile estimated based on the electrical usage behavior. The red and blue line represents the actual and synthetic load profile, respectively. The actual and synthetic load profiles represent the average hourly load consumption in a month (March 2017). Figure 8 shows that the time trend of the synthetic load profile and the actual load profile has a good agreement. This implies that the synthetic load consumption is almost similar to the actual load consumption. From the graph, the variation between the actual and synthesized load profile is larger during the off-peak as compared to the on-peak estimation. Figure 9 shows the estimation error of the synthetic load profile. The estimation error is calculated based on the difference between actual load consumption and synthesized load consumption. As seen in Figure 9, the highest estimation error is 8.5% at 12:00. The result implies that the FIS is able to estimate the synthetic load profile based on the electrical usage behavior model of the student. Next, various DSM techniques are applied to the proposed FIS and the corresponding synthetic load profile is analyzed to study the effectiveness of these techniques in reshaping the load profile by managing the student electrical usage behavior.

Table 1. The detail of the utilization of electrical appliances.

No.	Electrical appliances	Power rating (W)	No. of load
1	Lamps	36	1004
2	Fan	80	1080
3	Exhaust fan	61	32
4	Hair dryer	1200	120
5	Kettle	1200	825
6	Washing machine	700	6
7	Iron	1000	870
8	Laptop charger	45	1200
9	Phone charger	36	1185
10	Stand/table fan	58	210

Table 2. The electrical usage behavior.

Loads	Time																							
	Stage 1						Stage 2						Stage 3						Stage 4					
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
L1	N	N	N	N	L	N	N	L	L	L	L	L	L	L	L	L	L	L	H	H	H	H	H	N
L2	H	H	H	H	H	H	N	H	H	N	N	N	N	N	N	H	H	H	H	H	H	H	H	H
L3	H	H	N	L	L	N	H	H	H	H	N	N	N	L	L	N	N	N	N	H	H	H	H	H
L4	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L
L5	L	L	L	L	L	L	N	N	L	L	L	L	L	L	L	L	L	L	N	N	L	L	L	L
L6	L	L	L	L	L	L	H	H	H	H	H	H	L	L	L	L	L	L	H	H	H	H	H	H
L7	N	L	L	L	N	L	N	N	N	N	N	N	N	L	N	L	L	L	L	L	L	N	N	N
L8	N	N	N	N	N	N	N	L	L	L	L	L	N	L	N	L	N	N	L	N	L	N	N	N
L9	N	N	N	N	N	N	L	N	N	N	N	N	L	N	L	N	L	N	N	N	N	N	N	N
L10	H	H	H	H	H	H	H	H	H	N	H	N	H	H	H	H	N	N	H	H	H	H	H	H

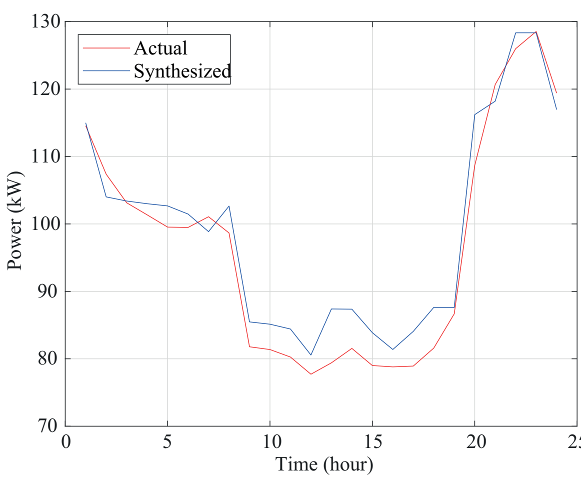

Figure 8. The actual load profile versus the synthetic load profile of student behavior.

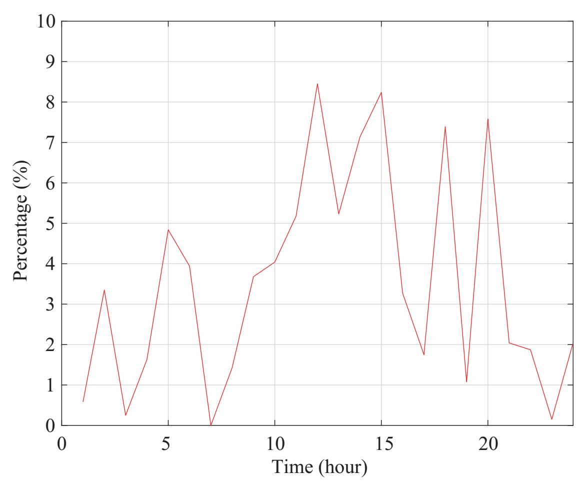

Figure 9. The synthetic load profile estimation error.

5. Performance evaluation of the proposed FIS in the DSM application

This section evaluates the performance of the FIS in estimating the synthetic load profile by applying the DSM technique to modify the electrical usage behavior of the student. The FIS only considers the electrical load behavior with the corresponding load profile behavior in the development process. Then, the DSM technique is applied to the proposed method by modifying the load behavior model accordingly. The FIS is utilized to estimate the corresponding synthetic load profile of the modified electrical usage behavior. From this study, the performance of various DSM techniques on the student can be compared and analyzed. In practice, there are six variants of DSM techniques available: peak clipping, load shifting, load conservation, flexible load, valley filling, and load growth. This study only considered the peak clipping, load shifting, and load conservation methods as shown in Figure 10. Each technique aims to solve different objectives with certain limitations. The load clipping aims to reduce energy consumption during on-peak load periods [21], the load shifting technique aims to shift the demand of customers from on-peak period to the off-peak period [22], while the load conservation techniques aim to reduce the energy consumption and need for electricity consumers as a whole [23]. At the distribution level, these objectives are achieved by manipulating the electricity tariff. However, the electricity tariff manipulation is not effective to the student as they are paying their electricity bill indirectly.

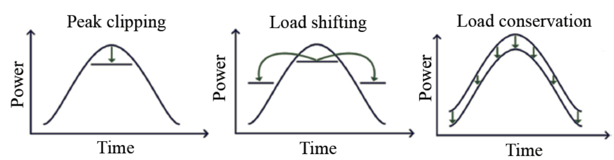

Figure 10. Demand side management techniques.

5.1. Load clipping

The load clipping implemented in this study represents the actual college program implemented in Tun Dr. Ismail Residential College, UTHM. The program is called the "Earth Hour Program", which is part of the college initiative to reduce the electricity bill of the university. In the program, the student is urged to turn off the light for one hour starting from 11 pm until 12 am. The online survey conducted in this study also evaluates the satisfaction level of the student towards this program. The study shows that 96.3% of students support this program as part of their contribution to combat climate change. The corresponding student behavior is modeled by modifying electrical usage behavior. The modified electrical usage behavior is applied to the proposed FIS to estimate the synthetic load profile with the load clipping technique. Figure 11 depicts the comparison between the actual average, the synthetic average, and the actual load profile with the application of the load clipping technique. Based on Figure 11, the red line represents the actual average hourly, the blue line represents the synthetic average hourly with the load clipping technique, and the green line represents the actual load profile of the "Earth Hour Program" conducted on the 19th March 2018. It is observed from the figure that there is a significant drop in load consumption of the synthetic average hourly load profile from 11 pm until 12 am. This drop is associated with the modification of the electrical usage behavior that represents the load clipping program. Then, the FIS is utilized to estimate the synthetic load profile based on the modified electrical usage behavior. Also, the actual "Earth Hour Program" load profile corroborated the trend shown in the estimated synthetic load profile.

5.2. Load shifting

The aim of the load shifting technique is to transfer the load from the on-peak to the off-peak period. The technique is a successful DSM technique in practice as the utility imposes a high tariff during the on-peak period and reduces the tariff at the off-peak period [24]. Consequently, the industry and commercial user shifts their business activities from the on-peak period to the off-peak period. However, it is very challenging to implement this technique to the student because the tariff manipulation is not effective to them. Therefore, the price is manipulated by changing the rate of laundry services used by the student as they are paying the service separately. The response from the online survey to the student shows that 97.5% of the respondent is willing to shift this activity to another period if the price package is attractive. Consequently, the electrical usage behavior is modified to shifting the laundry activities from the on-peak period to the off-peak period. Then, the modified electrical usage behavior is applied to the proposed FIS to estimate the synthetic load profile. Figure 12 shows the comparison between the actual load profile and the synthetic load profile with the load shifting technique. The red and blue lines represent the actual average hourly load profile and the synthetic average hourly load profile with the load shifting technique, respectively. In this discussion, there are divided into three parts, which represent on-peak and off-peak of the load usage. The result indicates the manipulation of the laundry service rate affects the load profile time trend. The result demonstrates the load consumption during the on-period is shifted to the off-peak period. This implies that the student shifts their laundry activities from the on-peak to the off-peak period.

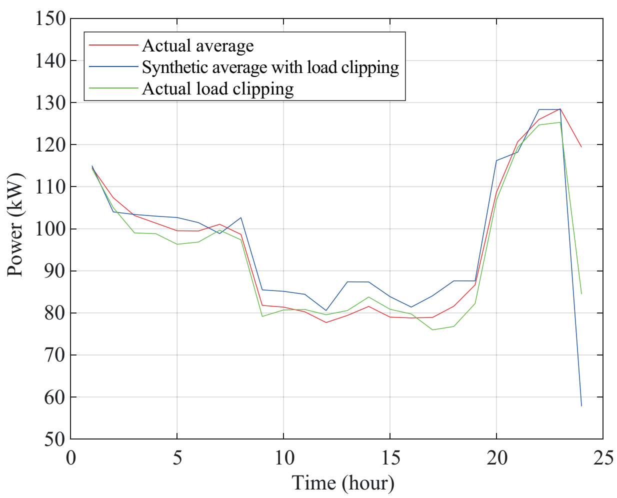

Figure 11. The actual average, the synthetic average with load clipping, and the actual load clipping.

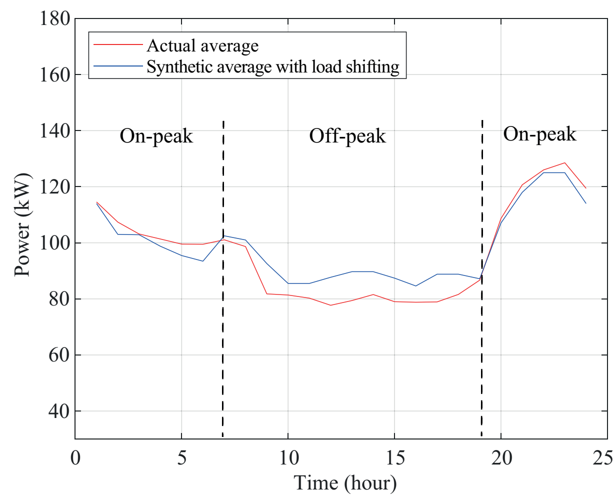

Figure 12. The actual average and the synthetic average load profile with the load shifting technique.

5.3. Load conservation

In this study, the lamp and fan are selected for the upgrade as they are the most utilized loads in the residential college. In addition, the replacement of these loads is within the college management authority. Following this change, the electrical usage behavior is modified and applied to the FIS to estimate the corresponding synthetic load profile. The challenge in implementing this technique lies in the huge capital expenditure required for the highly efficient appliance replacement. However, based on the online survey, 92.4% of students are willing to invest in this upgrade if there is any attractive refundable scheme program to recover their investment using the profit gained from the energy saving. Figure 13 shows the comparison between the actual load profile and the synthetic load profile with the load conservation technique. The blue and the red lines represent the actual average hourly load profile and the synthetic average hourly load profile with the load conservation technique, correspondingly. From the result, it is shown that the load conservation technique reduces the energy consumption for the entire period except at 12 pm. This characteristic is expected as the load conservation technique replaces the conventional lamp and fan to the appliances with higher efficiency. At 12 pm, the utilization of the lamp and fan are at the minimum. Therefore, the impact of the load conservation technique is also minimum at this time. This implies that the impact of the load conservation technique is directly proportional to the usage of these two appliances. Thus, it is also observed that the impact of the load conservation technique is the most significant during the peak of the load consumption.

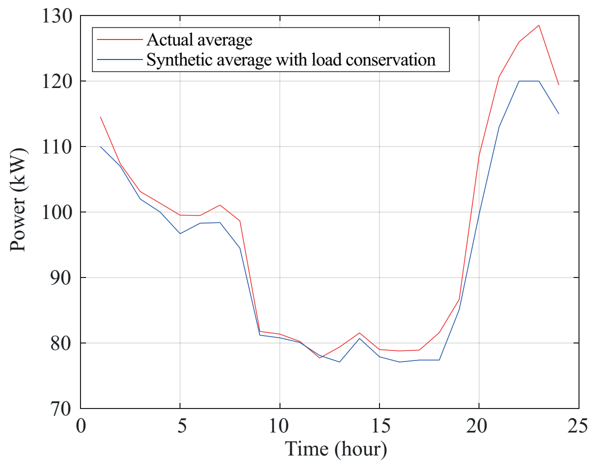

Figure 13. The actual average and the synthetic average load profile with the load conservation technique.

5.4. Comparison of DSM method

The DSM techniques comparison is presented in Table 3. The table shows the total energy consumption, total energy saving, peak power, and peak power reduction of all DSM techniques considered in this study. The total energy consumption of load clipping, load shifting, and load conservation are 2314.835 kWh, 2288.38 kWh and 2247.5 kWh, respectively. The result shows that the total energy saving contributed by each technique is 0.655 kWh, 27.11 kWh, and 67.99 kWh, respectively. The results imply that the load conservation technique outperforms the load clipping and the load shifting technique in this application. This indicates that the FIS technique can estimate the synthetic load profile accurately, even when the DSM techniques are applied. In this study, the potential energy savings by replacing the currently fluorescent lighting system with a modern LED lighting system is up to 56%. Meanwhile, the fan replacement with high efficiency saves about 28% of energy. In terms of investment perspective, the payback period of replacing the lamp alone is around 9 months, while the total payback period of replacing the fan alone is around 70 months. However, the combination of both lamp and fan replacement only requires around 36 months to regain the investment. This implies that the most attractive replacement plan is by replacing the lamp only. However, the replacement of both lamp and fan is still relevant for the student as the payback period is within the study-time length of an undergraduate course (3–4 years, depending on the type of program). It is noted that the payback period is calculated based on the effective tariff and the average cost of an LED lighting system and a highly efficient fan of the current market. Based on the survey conducted for this study, although the implementation of the conservation technique requires substantial capital expenditure, the residential college student is willing to invest if there is an attractive program to recover the investment is available.

Table 3. Comparison of DSM techniques.

DSM techniques	Total energy consumption (kWh)	Total energy saving (kWh)	Peak power (kW)	Peak power reduction (kW)
Load clipping	2314.835	0.655	128.348	0.192
Load shifting	2288.38	27.11	125	3.54
Load conservation	2247.5	67.99	120	8.54

The proposed FIS technique facilitates the performance evaluation of the DSM techniques to the student. The effectiveness of the DSM technique can be evaluated by modifying the electrical usage behavior of the student, and the corresponding synthetic load profile can be comparatively analyzed. The application of the FIS technique to estimate the synthetic load profile can be extended to other types of users, defined by various types of tariff. The proposed technique is beneficial to perform this study as the definition of tariff varies from one country to another. The results show that the FIS can estimate the synthetic load profile based on the electrical usage behavior model. The application of DSM modifies the electrical usage behavior and consequently, affects the corresponding load profile time trend. This implies that the proposed FIS can be used to create the digital twin of the residential college load consumption. By using the proposed technique, the performance of various DSM approaches can be analyzed first in the digital twin of the residential college load consumption prior to its implementation to the real-world. The outcome of this approach will help the decision makers to form intelligent solutions by identifying the most effective ways to reduce the use of energy consumption.

6. Conclusion

Conclusively, a novel approach to estimate the synthetic load profile based on the electrical usage behavior model using FIS is presented. The method models the electrical usage behavior based on the numbers of users, the user's schedule and activities, and the type of load. Then, the corresponding load profile is paired with the electrical usage behavior model as the input-output pairs to train the FIS. The result shows the FIS can estimate the synthetic load profile based on the electrical usage behavior model accurately. The effectiveness of the proposed method is demonstrated in a study case to evaluate the performance of DSM techniques to modify the load profile behavior of the student. This study case is essential in managing the load consumption in an institution where the student pays the electricity bill indirectly. Three types of DSM techniques, load clipping, load shifting, and load conservation, are applied to the proposed FIS, and the corresponding synthetic load profiles are comparatively analyzed. The results show that the FIS technique can estimate the synthetic load profile accurately, even when the DSM techniques are applied. Also, the conservation technique is the most suitable DSM method to reduce the peak load and energy consumption of the residential college student. Although the implementation of the conservation technique requires substantial capital expenditure, the residential college student is willing to invest if there is an attractive program to recover the investment is available. From this study case, the proposed FIS can be used to evaluate the performance of any DSM method to various types of users. The proposed methodology can be utilized as an analytical tool in the realization of the digital twin concept in the future smart grid advancement where the performance of the DSM technique is evaluated prior to its deployment in the real system.

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