Bulletin of Electrical Engineering and Informatics
Vol. 11, No. 2, April 2022, pp. 646~657
ISSN: 2302-9285, DOI: 10.11591/eei.v11i2.3556

Optimal load management strategy under off-peak tariff riders in UTeM: a case study

Mohamad Fani Sulaima[1], Musthafah Mohd Tahir[2], Aida Fazliana Abdul Kadir[1], Mohamad Firdaus Shukri[2], Mohd Rahimi Yusoff[3], Ainuddin Abu Kasim[4], Luqman Ali[4]
[1]Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia
[2]Faculty of Mechanical Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia
[3]Faculty of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia
[4]Office of Facilities Management, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

Article Info

Article history:

Received Aug 31, 2021
Revised Dec 6, 2021
Accepted Mar 15, 2022

Keywords:

Cooling system operation
Demand response
Demand side management
Energy management
Time of use tariff

ABSTRACT

Demand response (DR) program through tariff initiative has been established in Malaysia since 1990. The available time of use (TOU) tariff focuses on providing price signals to consumers, especially from industrial and commercial sectors. In achieving a certain standard for off-peak tariff rider (OPTR) initiative to receive discount rate, consumers must improve load factors compared to the baseline declared. However, not all consumers are able to commit. In Universiti Teknikal Malaysia Melaka (UTeM), the TOU (C1-OPTR) tariff is proposed and applied when the available cost discount of 20% can be enjoyed by sustaining the load factor improvement (LFI). A simulator projected a flexible optimal load profile referred by the energy management team to achieve the university's sustainable energy management goal. Thus, securing the LFI would allow the energy consumption (kWh) and peak demand (kW) to be managed concurrently. As for testing results for two buildings, the load factor improves to 0.40, and the maximum demand reduces by about 35 kW. When getting the 20% discount for the OPTR scheme, the total cost saving is forecasted approximately USD 29,441.40 yearly. The current pilot project presents a positive sign with the peak demand reduction and load factor improvement close to the simulator's optimal profile.

Corresponding Author:

Mohamad Fani Sulaima
Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka
Hang Tuah Jaya, 76100, Durian Tunggal, Melaka, Malaysia
Email: fani@utem.edu.my

1. INTRODUCTION

Synergy in load management strategy is crucial for managing the sustainable environment; while ensuring the activities reduce the generation tension. Thus, the peak power demand would be adequately managed by improving such holistic measures such as load factor on the consumers' side [1]. The critical issue of balancing power system supply under intelligence microgid has occured when demand side management program such as electricity tariff initiative is not designed comprehensively [2]. In Malaysia, the conventional TOU tariff is designed based on a two-time zone and has been updated to enhanced TOU tariff since 2014 [3]. In regards to the TOU and ETOU program, there were several studies have been reported. Research by Nazar *et al.* [4] reports that the demand response program through TOU tariff contributed to changing generation and demand side load profiles. The impact of the TOU tariff design to increase benefit to the energy provider and reflect the power delivery service was explained by Abdullah *et al.* [5]. The load profile changes to reflect the ETOU tariff discussed by Azman *et al.* [6], where the suggestion of the load management percentage to enjoy the proposed tariff is summarized accordingly.

In Peninsular Malaysia, commercial and industrial consumers from flat tariff of C1 and E1 categories are offered with off-peak-tariff rider (OPTR) scheme. The consumers will enjoy a twenty (20) percent discount for the off-peak time (2200-0800 AM) when they can improve the load factor. The load factor is the indicator for the excellent management of peak demand and balancing the optimal energy consumption management of consumers' demand side [7]. Ashok and Banerjee [8] used the daily energy consumption related to the load factor to assess the effectiveness of the LS strategy. The load factor improvement is an essential parameter since an improvement indicates a reduction in the peak demand, which will mitigate the total electricity cost. On the other hand, the program contributes to the reconfigured power distribution network to minimize power losses and maintain the system's reliability and stability to improve load factor by consumers of electricity [9]. Thus, consumers who can improve their load factor can benefit from their electricity purchasing since a high load factor (> 0.75) indicates that they maximize their electricity usage over the billing period set by the utility. As in Malaysia, to gain financial benefits from the TNB's TOU tariff scheme, consumers need to improve their load factor before being granted permission for tariff transform. However, fewer consumers can improve load factor when managing the maximum demand and energy consumption as reported [1]. Thus, in this study, the load factor index (LFI) was used to assess the cost-effectiveness of the load management (LM) strategies for UTeM to reflect an improvement of the generation efficiency by utilities.

Inline to the artificial intelligence technology to promote an optimal solution for complex problems. Challenge of the load management to reflect price signals such as the TOU scheme has contributed to the adaptation of bio-inspired algorithms to specific significant energy users [10], [11]. For example, BPSO was used as a control system to shift the schedule of the water heater. The performance of the genetic algorithm (GA) and PSO was compared to determine the optimal cost for heat pump and thermal storage scheduling. A study on the LM strategy was conducted in huge areas, including smart grid (SG) systems such as load shifting and optimization algorithms applied in pass literature. For instance, some research using the multi-objective optimization for consumers in SG homes to shift the load with the objectives to minimize electricity costs and time delay of home appliances [12], [13]. To reduce CO_2 emissions, generation cost, and electricity costs for consumers as the algorithm's objective function where the load shifting strategy was applied accordingly Tsagarakis *et al.* [14]. Meanwhile, the internet of things (IoT) application leads the current model towards advanced integration of load management and optimization algorithms [15]. In reflecting on previous studies about the TNB's TOU tariff in Malaysia, load management has adopted optimization algorithms to reduce the electricity cost while improving consumer satisfaction. For instance, the evolutionary algorithm (EA) and ant colony optimization (ACO) algorithm was applied to find the best load profile reflecting price signal under ETOU tariff scheme for the industrial consumers [16], [17]. Meanwhile, artificial neural network (ANN) method was applied to setting up the load curve to suit tariff time zones under the same scheme [18]. Nevertheless, there is less study focusing on OPTR-TOU scheme where the optimization algorithm is promoted to find the best arrangement of load profile while full-filling the requirement of the load factor to be improved concurrently.

On the other hand, the discussion on extensive energy data analysis advances most of the investigation. The consumers' and generation data are crucial for better future load profile forecasting, as reported by Majeed *et al.* [19]. The arrangement of the load management strategies to the system classification is vital for the energy market to improve while offering better tariffs for the consumers, especially those from the flat tariff. Hence, in line with the sustainable development goal (SDG: 7 and SDG: 9) and the spirit of advancing the demand side management solution, Universiti Teknikal Malaysia Melaka (UTeM) proposes an innovative solution for demand response programs such as the way to enjoy OPTR tariff initiative. Therefore, a demand response simulator was formulated based on a combination of optimization algorithms and load management strategies such as peak clipping, valley filling, and load shifting. Thus, the proposed project considered a world future integration demand side management component that simultaneously combines energy efficiency and demand response programs.

Figure 1 presents the general flow of the proposed method. The project hopes to benefit the sustainable energy management practice at the national, ASEAN, and international levels. The arrangement of the paper started with section 2 for the methodology of the project. Section 3 presents results and discussion of the project, while section 4 is the conclusion.

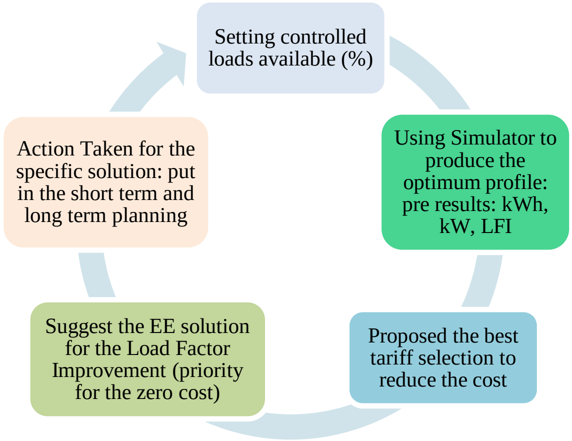


Figure 1. Effects of selecting different switching under dynamic condition

2. METHODOLODY

The formulation of optimal strategies considers valley filling, load shifting, and peak clipping into the simulator [1]. Meanwhile, the OPTR scheme tariff formulation is presented in (1). The OPTR in flatt tariff scheme electricity cost (USD) can be written as:

$$\mathrm{Flatt}_{\mathrm{cost}}^{\mathrm{OPTR}}=\mathrm{Optimal}_{\mathrm{eCost}}+\mathrm{MD}_{\mathrm{Optimum\ allocation}}^{\mathrm{Cost}} \tag{1}$$

where $\mathrm{Optimal}_{\mathrm{eCost}}$ is the electricity consumption cost of the desired load curve after the load management strategies are implemented, reflecting the base price of the two segments as presented in (2). Meanwhile, the arrangement strategy to mitigate the MD cost, $MD_{Optimum\ Allocation}^{Cost}$ is formulated in (3).

$$\mathrm{Optimal}_{\mathrm{eCost}}=\min \sum_{\mathrm{hour\ i=1}}^{\mathrm{N}} \frac{\mathrm{P_{total\ power\ consumption}} \times \mathrm{TP_{OPTR\ \&\ Flat}}}{24\mathrm{hours}})$$
$$= (\textstyle\sum_{hour\ i=1}^{10} P_{op} \times TP_{OPTR}) + (\sum_{hour\ i=1}^{14} P_p \times TP_p) \tag{2}$$

where: N: total number of the loads

P_{op}: optimum power consumption in the off-peak zone (desired load curve) concerning $hour\ i = 1$,

P_p: optimum power consumption in the peak zone (desired load curve) concerning $hour\ i = 1$.

TP_{op}: tariff price for off-peak time zone set followed standard OPTR scheme discount set by the utility

TP_p: flat tariff price for peak time zone set by the utility

$$MD^{charge} = \mathrm{Peak\ power\ (kW)}^{\mathrm{30\text{-}min\ interval\ (in\ a\ month)}} \times MD^{\mathrm{price\ by\ utility}} \tag{3}$$

The MD charge is vital in calculating the total electricity cost. In this study, $MD_{optimum}^{cost}$ was set as the variable for $Flatt_{Cost}^{OPTR}$, as indicated by (1). For this reason, it is necessary to allocate the peak demand in the proper allocation. In (4) shows the optimum MD charge obtained by sorting the MD charges outside the normal allocation of MD.

$$MD_{Optimum}^{Cost} < MD_P^{cost\ Current}, MD_P^{cost\ Reduction} \in MD_{Optimum}^{Cost} \tag{4}$$

where: $MD_P^{cost\ Reduction}$: optimum price of power load selection outside normal allocation of MD

$MD_P^{cost\ Current}$: price of power load selection in the peak area

The LFI was used to assess the sustainability of the OPTR tariff scheme programme. The LFI is given by:

$$LFI = \frac{\sum E_{TSn}}{MD_{Optimum}^{kW} \times day \times t} \times 100 \tag{5}$$

where, $\sum E_{TSn}$ is the total electricity consumption for n time segments, t is the time of electricity usage, and $MD_{Optimum}^{kW}$ is the optimal selected MD in kilowatts (kW) in the peak or mid-peak time segment. The LFI is set between 0 to 1. The value close to 1 indicates the excellent index of load factor which the energy consumption and maximum demand is manage properly. The total energy consumption different before and after optimization and implementing the LM strategies should not be more than ±5%. The optimization algorithm must be flexible during the simulations and thus, this value is considered reasonable based on the standard reference settings for load profile approximation [20]. The total energy consumption in kilowatt-hours (kWh) before and after applying the optimization algorithm is given by:

$$\sum E_T \approx \sum E'_T \quad (6)$$

The simulator has adopted particle swarm optimization (PSO) algorithm to search for the best load profile with the output of load factor improvement and minimum electricity cost. Details explanation of the PSO implementation is demonstrated by:

2.1. Initialization

The PSO algorithm begins with initializing the number of particles *D* and the number of populations *NP*. In this study, *NP* was set as 20. The initial number of particles *D* was determined by calling the load profile that represents the daily average 24-h energy consumption, which was randomly generalized. In (7) shows the initial condition of the load arrangement. The constant parameters such as the social and cognitive coefficients were set at 1.0, and the initial weight coefficient was set at 0.2. The maximum inertia, minimum inertia, and the number of iterations were set at 0.9, 0.1, and 1000.

$$j=[j_{x1},j_{x2},j_{x3}\ldots\ldots\ldots\ldots j_{xn}] \quad (7)$$

2.2. Velocity and position update

The initializing number of (8) and (9) were used to update the position and velocity of the particles, respectively.

$$x_i(t+1)=x_i(t)+v_i(t+1) \quad (8)$$

$$v_i(t+1)=v_i(t)+C_1\left(\vec{P_i}(t)-\vec{x_i}(t)\right)+C_2(G(t)-\vec{x_i}(t) \quad (9)$$

The modified velocity and inertia weightage been applied in immense power [21] and energy related studies such as integrated demand response [22], home energy management [23], power network reconfiguration [24] and load scheduling in manufacturing [25]. The modified velocity and inertia weightage of PSO was used to improve the optimal solution for the complex problem. In (10) represents the inertia weightage. The value for ω was set between 0 and 1, and it is the so-called friction factor. The inertia weightage is used to ensure that the particles remain in the original course. Thus, the particles do not affect the motion of other particles (by pulling other particles into their path) and preventing oscillations around the optimal value. In (11) is used to update the velocity of the particles in the standard PSO algorithm, and stimulate the vector movement of the particles. In the simulator, the particles' velocity and position were updated according to (12) and (13); respectively, the local and global best were allocated to produce a clear presentation.

$$\omega(n)=\omega_{max}-\left(\frac{\omega_{max}-\omega_{min}}{iter_{max}}\right)\times n \quad (10)$$

$$v_{ij}(t+1)=\omega v_{ij}(t)+r_1C_1\left(\left(P_{ij}(t)-\ x_{ij}(t)\right)+r_1C_2\left(G_j(t)x_{ij}(t)\right)\ \right) \quad (11)$$

$$V_j^{k+1}=\left(\omega\times V_j^k\right)+\left(C_1r_1\left(P_{bestj}^k-X_j^k\right)\right)+\left(C_2r_2\left(G_{bestj}^k-X_j^k\right)\right) \quad (12)$$

$$X_j^{k+1}=X_j^k+V_j^{k+1} \quad (13)$$

Where, V_j^k is the velocity of particle j in iteration k while X_j^k presents the position of particle j in iteration k. P_{bestj}^k is the best value by particle j in iteration k and G_{bestj}^k is best value among the fitness values. Meanwhile, inertia weightage and constants factor from zero to one are presented by ω, C_1 and C_2, respectively. Finally, the new position of the particles is presented by X_j^{k+1} while new velocity demonstrates by V_j^{k+1}.

2.3. Determine P_{best} and G_{best} and update the new velocity and position of the particles

During the searching process, the two best values were updated and recorded. The P_{best} and G_{best} represent the best energy consumption cost and optimum MD cost generated during the execution of the algorithm, respectively. In this step, the particle's current fitness value was compared with the particle's P_{best}. If the current fitness value was better than the P_{best} value, the P_{best} position was adjusted to the current best position. The same procedure was performed for G_{best}, where the G_{best} the value was reset to the current fitness value, representing the optimal daily energy consumption cost, the minimum MD charge and load factor improvement. The new velocity and position were updated in each iteration according to (12) and (13).

2.4. Convergence test

The convergence criterion was set as:

$$ft\_max\text{-}ft\_min \leq 0.0001 \tag{14}$$

This termination criterion was used to determine if the desired optimal solution was achieved. The searching process will be repeated until the values converge to the optimal load curve with the minimum energy consumption cost, minimum MD cost, and load factor improvement. Hence, Figure 2 (in Appendix) shows the project flow to get optimum benefits from the OPTR tariff scheme for the university. Details information of the load has been assessed through the energy management team of the university while the results from energy audit program was utilized to find the best percentage of the load could be controlled. Apart of that, initial baseline data was collected from IoT monitoring system installed in the main circuit breaker room. The available data of the energy profile is used for the simulation process in the simulator before the site testing of load management activities. Since UTeM is currently using buildings management system (BMS) to control the most significant energy user such as cooling system operation (CSO), the simulator output results have been used to strategically suit CSO's operation. Initial the rest of the project implementation would be referred to the Figure 2 congruently.

3. RESULTS AND DISCUSSION

3.1. Case study

Energy management committee (EMC) has decided to test the load management strategy of the optimal cooling operation at two buildings which are Faculty of Technology Multimedia and Communication (FTMK) and Laman Hikmah Library (LHL), simultaneously. Therefore, load verification was carried out by load apportioning and identifying whether the buildings' loads were static or non-static loads. Figure 3 shows the power consumption breakdown after load apportioning. The operation of the approximate chillers constituted the highest power consumption (57.68%), while the air-handling unit (AHU) consumed 11.92% to be significant dynamic loads for the buildings. Meanwhile, the rest of the load's types were plug load (10.22%), server room (0.4%), and unclassified load (others: 1.02%).

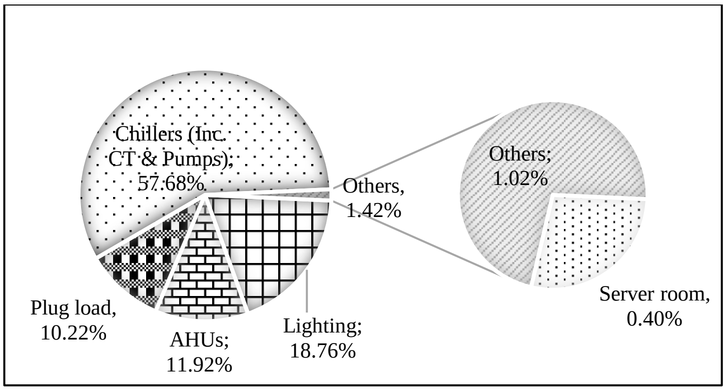


Figure 3. Load apportioning for the buildings

Thus, Figure 4 demonstrates the location of the case study buildings in the UTeM main campus, with the breakdown of buildings' energy consumption, was about 18%. Facilities consist of centralize chillers plant, AHU, fan coil unit (FCU), split unit air-conditioning types as the cooling system operates. As for the baseline (regular operation) condition and the tariff scheme information, Table 1 can be referred.

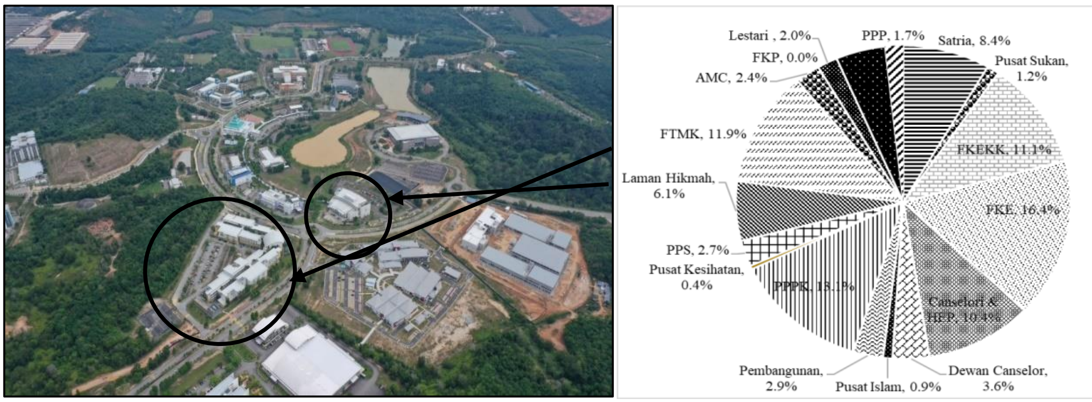


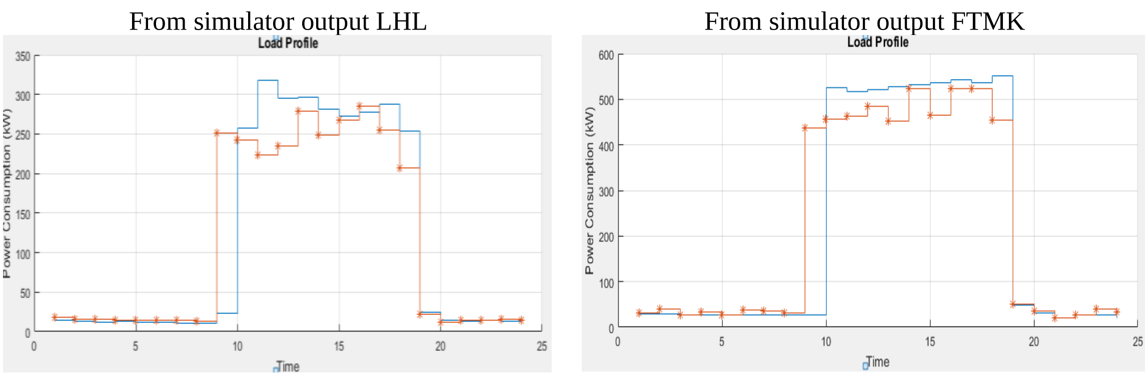
Figure 4. Location of the buildings and breakdown percentage to the total energy consumption

Table 1. Time of use (TOU) C1-OPTR tariff structure and baseline scenario

Tariff structure	Operation of cooling system	Setting temperature	Schedule for flexible working hours (staff)
C1-OPTR Tariff Scheme: Peak Tariff: 0.091(USD) per kWh Off-Peak: 0.073(USD)* per kWh Maximum demand: 7.575USD per kW *If load factor improves from the base value set by utility, 20% discount for the off-peak (10:00 PM to 8:00 AM) would be given	08:00 AM to 05:00 PM	24ºC±1ºC	07:30 AM to 04:30 PM; 08:00 AM to 05:00 PM; 08:30 AM to 05:30 PM

3.2. Optimal load profiles

From the involvement of the artificial intelligence simulator, the load profile findings for two buildings are presented as in Figure 5(a) and Figure 5(b), respectively. The baseline data was taken from the IoT monitoring system, which is the average profile for at least two weeks on regular working days. It was observed that, for the LHL building as presented in Figure 5(a), the spike has happened during the morning period during cooling started to operate. The peak demand for the LHL building was at 10:00 AM. However, as presented in Figure 5(b), the FTMK's buildings' peak demand happened at 17:00 PM that culminating in the operation of the facilities reflect the teaching and learning process activities.



(a) (b)

Figure 5. The comparison of load profiles from simulation output by IoT monitoring system for (a) forecast LHL optimal load profile and (b) forecast FTMK optimal load profile

Regarding simulator output for both buildings, the load has been suggested to be shifted to the area of off-peak zone reflecting C1-OPTR tariff scheme. The most significant load is proposed to be started early, around 6:30 to 7:00 AM, to enjoy a cheaper tariff rate while balancing the load factor's formulation and reducing the maximum demand value. The simulation results show the load should be decreased gradually after 3:30 PM. Since the cooling system (chillers and AHU) composed about 65% loads as a majority for the buildings, the operation team decided to manage the load by controlling them.

The system has followed an optimal simulation profile to effectively manage the cooling load, which should be started early, around 6:30 AM to 7:00 AM. Thus, the university operation is conducive for clocking in at 7:30 AM since flexible working hours have been introduced. The encouraging factor to work early in the morning would benefit the UTeM as OPTR discount would be enjoyed in the best way.

By referring to the actual testing load profile results for those buildings as in Figure 6(a) and Figure 6(b), the cooling system has started at 7:30 AM instead of 8:00 AM. In addition, for LHL power consumption profile that has presented in Figure 6(a), the temperature setpoint is set to 25ºC from 7:30 AM to 1:00 PM instead of 23ºC, which has reduced the cooling load by optimal adjustment of the control valve). Thus, the chiller will achieve setpoint temperature early due to the low indoor temperature in the morning.

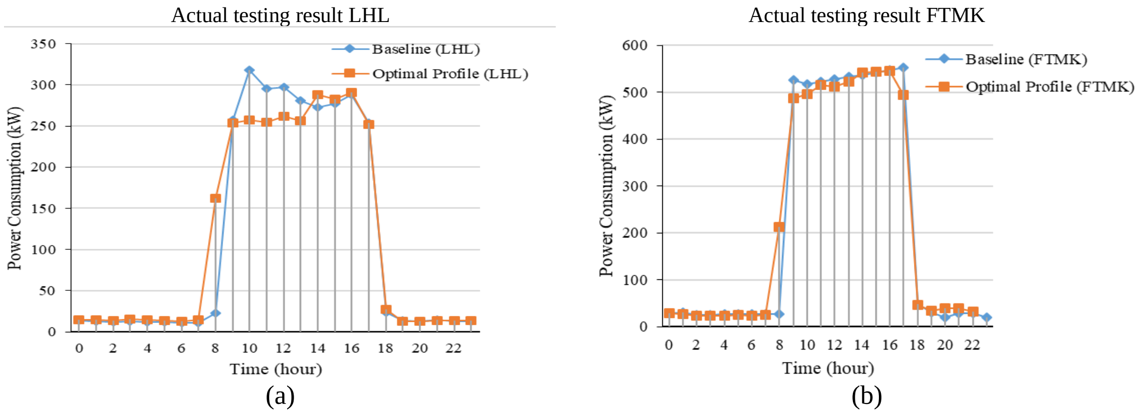


Figure 6. The comparison of load profiles of actual testing results recording by IoT monitoring system for (a) actual LHL optimal load profile and (b) actual FTMK optimal load profile

For FTMK refer to Figure 6(b), the temperature setpoint is set to 25ºC from 7:30 AM to 1:00 PM instead of 22ºC to reduce the cooling load by optimal adjustment of the control valve in AHU rooms. However, the temperature has been decreased gradually to the baseline setting after lunch hour to the central circulation of cooling air in the building. One chiller has been shut down early at 4:30 PM instead of 5:00 PM, reflecting suggestion operation by the operator. Using the setting of cooling temperature as two scheduling methods in BMS, the peak demand reduces dramatically while cost-saving through OPTR tariff scheme is achieved strategically. The operation setting in BMS could be used as the standard operating procedure for the buildings and the cooling system operation setting.

Table 2 summarizes the simulation and actual testing results to simultaneously reduce the peak demand and improve the load factor. The different load factor improvement percentage for FTMK was slightly but still able to give impact to benefit the OPTR scheme. The load factor still improves from 3.9 to 4.0 after actual testing. As a result, the peak demand reduction is countered for about 7 kW, but the energy consumption increases by 1.4%, respectively. On the other hand, the LHL simulation and actual testing results demonstrated good values. It was observed that the load factor improvement is equal to 9%, and the maximum demand reduction is approximately 27-33 kW for both conditions. Therefore, the energy consumption to the baseline reduces by about 0.47% to support the reduction of CO_2 emission too.

3.2. Electricity cost reduction

The load management strategy was applied to the cooling operation system of the buildings, where the impact of the cost reduction is presented in Figure 7 accordingly. In Figure 7(a), the simulation results predicted about 14% or USD 38,174.40/year saving before the actual load management project would be tested. However, in Figure 7(b), the actual achieved 10.5%, which is slightly lower than the forecasting simulation result. The actual cost after test was predicted to be USD 29,441.40/year. As the load management strategy's overall performance reflects the price signal under OPTR tariff scheme, the project could be considered successful where the simulation optimal load profile idea was finally released by actual testing action for the significant energy user in the building's operation. The adoption of an optimization algorithm such as PSO has contributed to the excellent results while the integration of the energy management procedure is another process to the achievement of the cost-saving.

Table 2. Comparison of simulation and actual testing results

Simulation results		Actual testing results	
FTMK	LHL	FTMK	LHL
i) Relative energy consumption to baseline (%): 0.86	i) Relative energy consumption to baseline (%): -1.6	i) Relative energy consumption to baseline (%): 1.4	i) Relative energy consumption to baseline (%): -0.47
ii) Maximum demand reduction: 28 kW	ii) Maximum demand reduction: 33 kW	ii) Maximum demand reduction:7 kW	ii) Maximum demand reduction: 27 kW
iii) Baseline load factor: 0.39	iii) Baseline load factor: 0.36	iii) Baseline load factor: 0.39	iii) Baseline load factor: 0.36
iv) Optimal load factor: 0.42	iv) Optimal load factor: 0.40	iv) Optimal load factor: 0.40	iv) Optimal load factor: 0.39
v) Load factor improvement (%): 6.1%	v) Load factor improvement (%): 9.7%	v) Load factor improvement (%): 2.7%	v) Load factor improvement (%): 9.2%

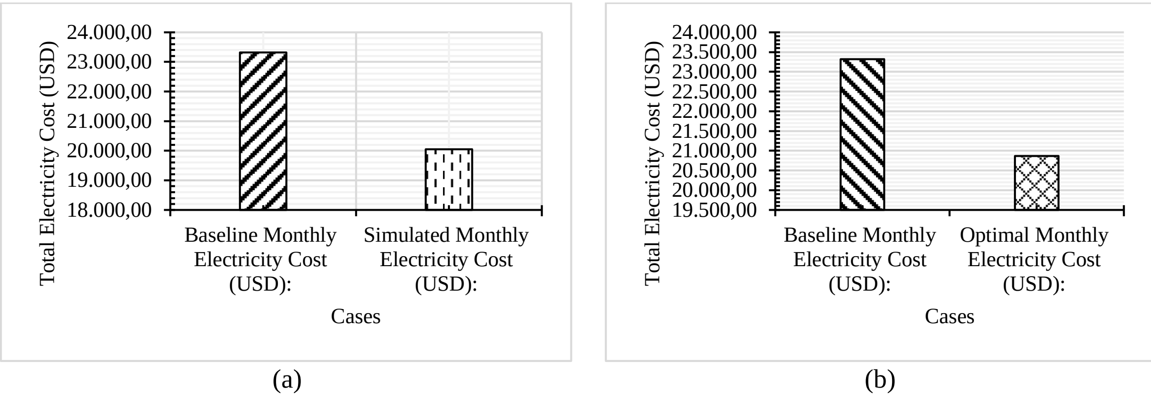


Figure 7. The simulation electricity cost and actual testing output cost were compared for the proposed load management strategy applied in LLH and FTMK (a) simulation output cost and (b) actual testing output cost at the buildings

4. CONCLUSION

To date, the consistency of the load factor value has been maintained as the indicator for achieving sustainable energy management in the university. In this project, the setting of the baseline load factor is around 0.36-0.39 has improved to earn an average maximum of 0.40 a year. The reduction of the maximum demand contributes to the excellent improvement of load factor. The proposed simulator to produce a reference load profile has given such an advantage for the university where the energy management team could plan for the load management strategies under demand response and energy efficiency program concurrently. The adoption of the PSO algorithm to produce forecasted optimal load profile under OPTR scheme able to be expanded for the other buildings and details integration to the sustainable energy management system would be done in the near future. The recommendation of further research would be focused on the different tariff types and another segment of the consumers, such as industrial type of tariff and specific operation and also for the residential consumers.

APPENDIX

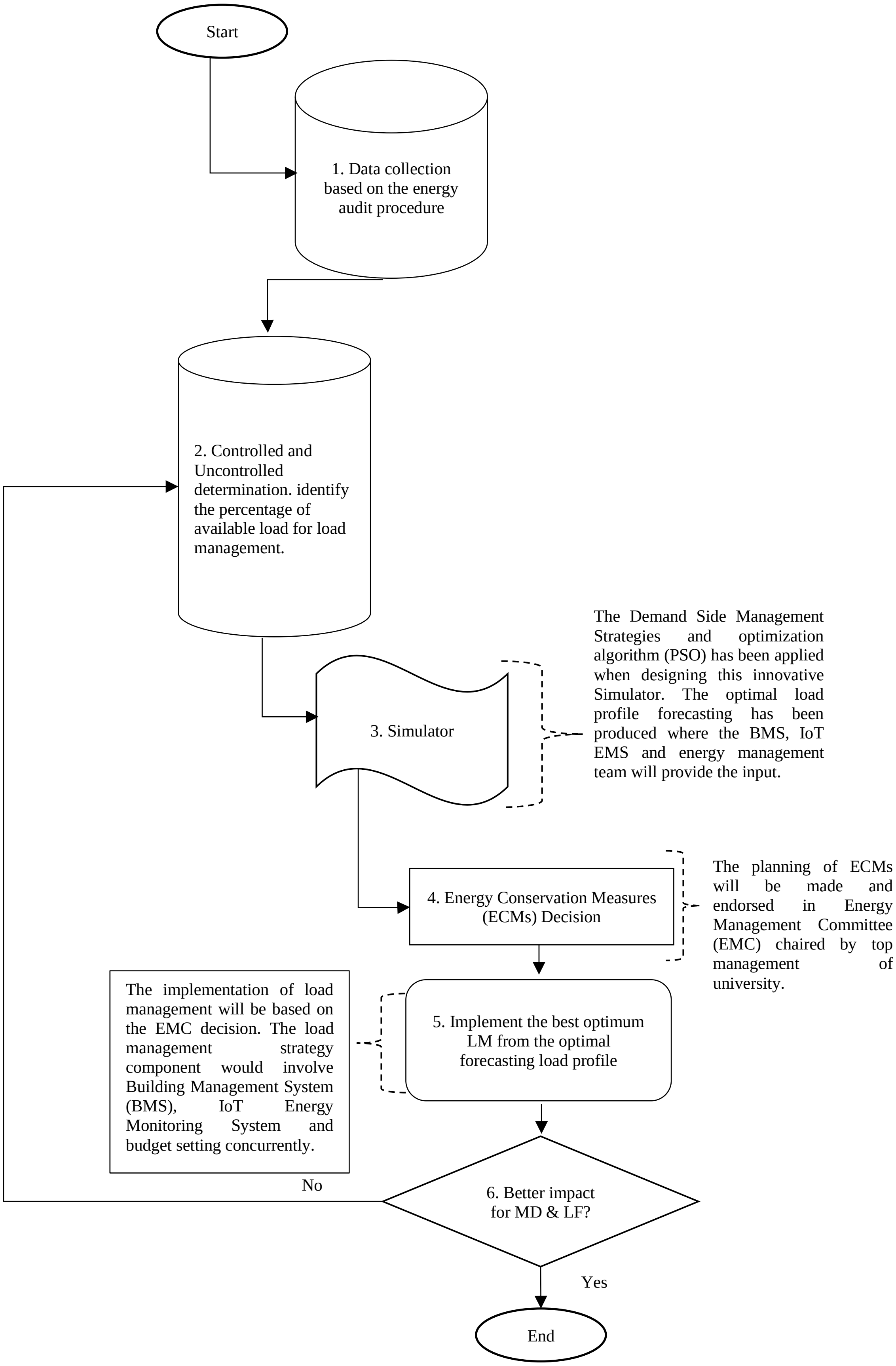


Figure 2. Proposed operation procedure to find the best MD and LF to be monitored

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BIOGRAPHIES OF AUTHORS

Mohamad Fani Sulaima is serving as Senior Lecturer in the Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka (UTeM). Upon joining UTeM, he served as a Coordinator and Head for the Energy Management Division in the Centre for Sustainability and Environment before being appointed as the first internal University Energy Manager in 2015. He received his bachelor's degree from Tokai University, Japan, in 2010 and a Master's degree from the University of Malaya. He received Ph.D. in Electrical Engineering with a specialization in Energy Demand Side Management from Universiti Teknologi Mara (UiTM), Malaysia, in 2020. His research interests include power system, demand-side management, demand response, energy efficiency, measurement & verification, and artificial intelligence. As a result of his research interest, he has published more than 90 articles, journals, and academic papers. He can be contacted at email: fani@utem.edu.my.

Musthafah Mohd Tahir is an Associate Professor in Faculty of Mechanical Engineering at Universiti Teknikal Malaysia Melaka (UTeM). Bachelor of Engineering degree from Electro Communication University, Tokyo in 1991. Master of Engineering degree in Mechanical Engineering in 1997 and PhD degree in Energy and Environmental Science in 2010, both from Nagaoka University of Technology. He is currently the Deputy Director at Centre for Sustainability and Environment, UTeM. A Registered Electrical Energy Manager of Malaysia Energy Commission since 2017. His current research interest includes internal combustion engine, heat transfer, energy management, battery charging and renewable energy. He can be contacted at email: musthafah@utem.edu.my.

Aida Fazliana Abdul Kadir received a B.Eng in Electrical from Univ. Teknologi Malaysia in 2000, an M.Eng. degree in Electrical from Univ. Teknologi Malaysia, in 2003 and a Ph.D. in Electrical Engineering in the Universiti Kebangsaan Malaysia (UKM), Malaysia. She is currently a Senior Lecturer at the Department of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia. Her research interests include Power System and Power Quality, Distributed Generation and Energy Efficiency. Ir. Dr. Aida Fazliana is a registered professional member of the Board of Engineers Malaysia (BEM) and member of the Institute of Engineering and Technology (IET,UK). She can be contacted at email: fazliana@utem.edu.my.

Mohamad Firdaus Sukri Bachelor of Engineering (Mechanical) with Honors from Universiti Teknologi Malaysia (UTM) in 2005, MSc in Manufacturing Systems Engineering from Coventry University, UK in 2007 and PhD in Mechanical Engineering from UTM in 2017. He is currently a senior lecturer in Universiti Teknikal Malaysia Melaka (UTeM) under the Faculty of Mechanical Engineering. He is also a Coordinator of Energy Management (Zone 1) of UTeM since January 2019. His main research interest includes energy efficient building, energy management and air conditioning and mechanical ventilation. Dr. Mohamad Firdaus Sukri is Certified Energy Manager under Asian Energy Management Scheme (AEMAS), Registered Electrical Energy Manager (REEM) under Energy Commision of Malaysia and Chartered Engineer (CEng) under Institution of Engineering and Technology, UK (MIET). He can be contacted at email: mohdfirdaus@utem.edu.my.

Mohd Rahimi Yusoff is an Associate Professor in Faculty of Electrical and ElectronicEngineering Technology at Universiti Teknikal Malaysia Melaka (UTeM). He received his B.Eng (Hons) in Electrical & Electronics Engineering from University of Wales, Swansea UK in 1990 and Master Degree in Electrical Engineering from University of Nottingham, England in 1992. He is currently an Assistant Vice-Chancellor, Development and Facility Management for the Universiti Teknikal Malaysia Melaka (UTeM). His research interest is power drive technology, facility management and sustainable energy and environment. He can be contacted at email: rahimi@utem.edu.my.

Ainuddin Abu Kasim currently hold the position as Director of Facility Management Office in Universiti Teknikal Malaysia Melaka (UTeM) with over 20 years of experience in university's development, operation and maintenance. Graduated with Bachelor's Degree of Engineering (Mechanical) with Honors from Universiti Teknologi Malaysia (UTM) in 2001 and Masters Degree of Environmental Management from Universiti Kebangsaan Malaysia (UKM) in 2017. Started his career as project engineer in a local oil and gas company before joining UTeM in March 2002 as Mechanical Engineer. He has huge interest in area of environmental sustainability and in occupational safety and health which ties to his responsibility as facility manager. He has been actively involved in many sustainability initiatives at university level throughout his employment. He can be contacted at email: ainuddin@utem.edu.my.

Luqman Ali is serving as Head of Mecahnical and Electrical Divison in Facilities Management Office, Universiti Teknikal Malaysia Melaka (UTeM). Upon joining UTeM, he served as an engineer for Mechanical Unit before promoted to Head of Department in 2020. He received his bachelor's degree from Kumamoto University, Japan, in 2012. Luqman Ali is Certified Energy Manager under Asian Energy Management Scheme (AEMAS) and Registered Electrical Energy Manager (REEM) under Energy Commission of Malaysia. He can be contacted at email: luqman.ali@utem.edu.my.