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MALAYSIA RESIDENTIAL LOAD PROFILE MANAGEMENT BASED ON TIME OF USE TARIFF USING ANT COLONY OPTIMIZATION ALGORITHM

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Abstract: In Malaysia, electricity generation has been rapidly increasing, in line with consumers' electricity demand. For those reasons, the government has introduced Demand Side Management (DSM) as a programme to promote balanced energy use between energy generation and demand. However, such an energy management policy is usually geared towards industrial and commercial consumers' but rarely towards residential consumers. The significant incentive demand response programme under the DSM, such as Time of Use tariff (TOU), was not implemented for residential consumers due to many reasons. These include the insufficient TOU tariff designs for residential use and the lack of awareness among consumers on how to manage their load profiles so that they couldn't enjoy concurrent reductions on their electricity bill. Thus, this study, aims to investigate what the best model of TOU time segmentation was for the residential consumers in Peninsular Malaysia. It also engaged in significant analysis to determine the optimal Load Profile Management (LPM) strategies for consumers that best reflected the residential TOU tariff. To determine the LPM this study made use of optimisation algorithms such as Ant Colony Optimisation (ACO); and an analysis comparing the performance of different load shift weightages that reduce the total cost of electricity are also considered and presented. A command average residential load profile has been tested as a real case study. The results of this study would help electricity providers to design a good TOU tariff policy and consumers would be able to benefit from the practice of LPM.

Keywords: Demand Side Management, time of use tariff, load profile management, Ant Colony Optimization.

Introduction

In Peninsular Malaysia, residential consumers are the most significant consumers of electricity, accounting for ~80% according to an announcement by the Energy Commission (Malaysia), 2019. The total increase in commercial and residential demand for electricity has grown by 53.7% from 2000 to 2015 (Kwong *et al*., 2018).

Since the demand has upsurged rapidly, the cost of the generation has increased and this situation has affected the price of the electricity for the end consumers. The increasing electricity bills have caused apprehension among consumers who have expressed a desire to reduce their electricity costs.

For this reason, Demand Side Management (DSM) was introduced. DSM refers to programmes that attempt to influence consumers' electricity consumption patterns to match current or projected capabilities of the power supplier (Strbac, 2008). DSM consists of three major components i.e. Demand Response, Energy Efficiency and strategic load growth as shown in Figure 1.

Demand Response (DR) which is the focus of this study, means the changes in energy usage on the demand-side from a typical profile of electricity usage in response to the price of electricity within a time frame (Meyabadi & Deihimi, 2017). There are two types of demand response programmes which are Market-based Programmes and Reliability-based Programmes.

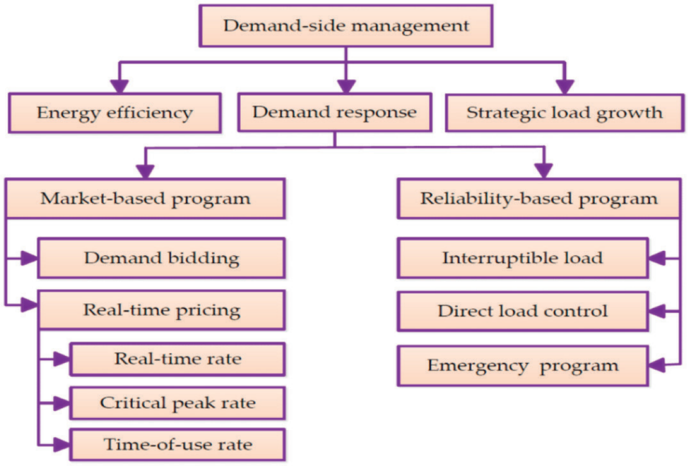

Figure 1: Components in DSM

In reliability-based DR programmes, consumers participate voluntarily or involuntarily to decrease their loads by controlling their appliance use. On the other hand, providing real-time electricity market prices through market-based DR programmes could provide consumers with the option to adjust electricity consumption. There are several types of pricing mechanisms that could be offered by utility companies such as Real-time Rates, Critical Peak Rates and Time of Use (TOU) Rates.

Since the government of Malaysia announced a reworking of the energy market policy, studies on the TOU tariff for residential consumers should be seriously taken into consideration. The effect of the residential loads to the generation accounts for and requires between ~20 and -30% of the price gap between peak and off-peak times has been considered by Muzmar *et al*. (2015).

The price signal setting from the utility was outstanding, while an affordable rate should also cover all costs including the operational expenditure (Opex), the money a company spends on an ongoing, day-to-day basis in order to run a business or system and the capital expenditure (Capex), money invested by a company to acquire or upgrade fixed, physical, non-consumable assets in power systems management.

The TOU tariff time zones referred to in this study were based on the average residential power demand in Peninsular Malaysia and was first proposed by Hussin *et al*. (2014). The generation side has been proven to gain benefits from the prototype design of the TOU tariff, while consumers should be able to shift the operation of their home appliances to achieve economic effectiveness.

Hence, in parallel with the advancement of artificial intelligence, the Load Profile Management (LPM) framework of optimum electricity costs to the residential consumers has been given a boost.

The optimisation of the LPM process using fuzzy and neural networks was adopted from by studies in Khorsandi and Cao (2016) and Barelli *et al*. (2018). The applicable loads involved in the LPM were decided using the optimum arrangement of the loads as a result of the peak demand reduction through load shifting strategy.

Non-linear programming was applied in Ampimah *et al*. (2018) and Oprea *et al*. (2018) to mitigate the burden cost to residential consumers by implementing a properly designed TOU tariff. A meta-heuristic algorithm was implemented in AboGaleela *et al*. (2012) and Sulaima *et al*. (2019) to show the effectiveness of the TOU tariff at meeting its objectives and the many benefits that accrue to the end consumers and supply providers.

The ability of bio-inspired algorithms such as Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO) among others, have also been used to great effect and contributed significantly to the comprehensive findings of the economic efficiency of the DSM in these studies.

With regards to the Malaysia electricity market condition, the authors in Azman *et al*. (2018) proposed 12-time zones for the TOU tariff and were concerned that the previous TOU design did not have much of an impact on the savings of the consumers. Nonetheless, the multi zone price signal risks upsetting the present market model and the sustainability of the demand response programme since not all consumers are able to manage their loads efficiently.

As mentioned by B. Parrish *et al.* (2020), the motivation of the consumers to join the demand response programme depends on the offer such as price rates, time zone allocations of the TOU tariff and the agreement period.

However, previous studies do not even consider the correlation or attempt to improve the load profiles of the consumers where the optimisation techniques could be applied to produce an optimum load curve reflecting the TOU tariff.

This study aims to consider the opportunity and the continuity of the TOU tariffs and believes that an optimisation algorithm would be the best technique to propose in order to allow the TOU tariff to have the best possible impact on consumers and chance at success. To date there is little reference available regarding the engagement of optimisation algorithms for residential consumers in the Malaysian electricity market.

This study aims to evaluate the effectiveness of the TOU tariff on the consumers' side. It also applied the ACO algorithm to the LMP to check and improve efficiency. The percentage of the load of the appliances involved in the LPM was considered too.

The research paper was then arranged in the following manner; Section 2 presented the problem with the TOU tariff structure formulation, Section 3 discussed the ACO algorithm engagement flow in finding the electricity cost reduction, while Section 4 analysed the results. Finally, the conclusions drawn from the data presented in this study was discussed in Section 5.

Problem Formulation

Figure 2 shows the average 24-hour electrical load profile of a selected residential area in Malaysia Muzmar *et al*. (2015). An early observation finds that the load pattern reaches its maximum demand from 9.00 pm until 11.00 pm because most people were at home during these hours.

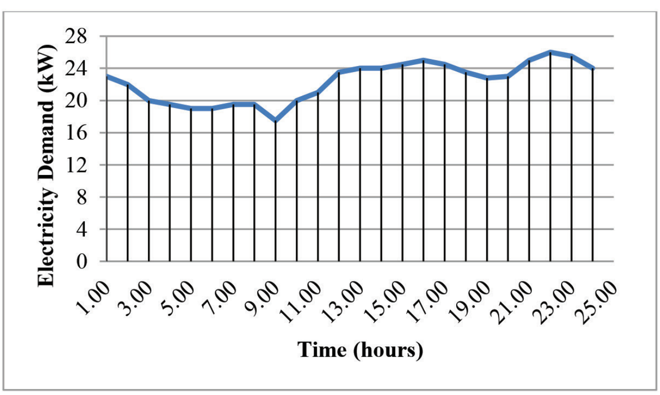

Figure 2: Electrical demand for a selected residential area in Malaysia

On the other hand, the electricity consumption was lower from between 8.00 am and 10.00 am because most of the people were at work. The TOU rates must be properly designed so that the consumers will be willing to reduce their electricity consumption rates during peak hours or shift it to off-peak hours in a bid to reduce their electricity costs.

These behavioural changes would reduce peak demand on the system from between 9:00 pm and 11:00 pm. In this study, it is assumed that the peak tariff was imposed on the residential consumers when the consumption is at its high that is between 6.00 am and 8.00 am and between 8.00 pm and 10.00 pm, while the off-peak tariff times were the remaining hours of the day (Hussin *et al*., 2014).

So, the formulation to determine the total electricity cost in the Time of Use (TOU) model is presented in equation 1.

$$TOU_{TC} = (L_{op1} \ x \ T_{op}) + (L_{p1} \ x \ T_p) + (L_{op2} \ x \ T_{op}) + (L_{p2} \ x \ T_p) + (L_{op3} \ x \ T_{op}) \quad \textbf{(1)}$$

where L_{op} is the total power consumption for off-peak time, L_p is power consumption at peak time which has been calculated based on residential load profile. TOU_{TC} is the total cost for TOU rates based on the two types of zones, T_{op} is the rate for off-peak time and T_p is for peak time. In the TOU model the optimum load profile and time segmentation were included, which was divided into five segments as given in equation 2 below.

$$TOU_{min} = \Sigma_{t=1} ((L_{op1} - (P_{op1} \times W))^2 \ x \ T_{op}) + (L_{p1} - (P_{p1} \times W))^2 \times T_p) + (L_{op2} - (P_{op2} \times \mathrm{W}))^2 \times \mathrm{T}_{op}) + (L_{p2} - (P_{p2} \times W))^2 \times T_p) + (L_{op3} - (P_{op3} \times W))^2 \times \mathrm{T}_{op}) \quad \textbf{(2)}$$

where TOU_{min} is the minimisation of actual power consumption to the desired load curve for the five segments of the TOU time frame. P_p and P_{op} are the total desired power consumption after optimal consideration of each segmentation. From equation 2, P_{op} represents off-peak power while P_p is peak power. W is the weighted factor of the load shifting based on the controlled and uncontrolled load finding based on the consumers' appliances.

The analysis is carried out by different values of the weighted factors which are W=5%, W=10%, W=15%, and W=20%. On the other hand, the constraints of the different total of energy before and after optimization must be equal as the minimum and maximum consideration is ±5%. Equation 3 describes the constraints as follows:

$$E'_1 + E'_2 + E'_3 + E'_4 + E'_5 \approx E_1 + E_2 + E_3 + E_4 + E_5 \quad \textbf{(3)}$$

Implementation of Ant Colony Optimization (ACO) Algorithm

ACO is inspired by the foraging behaviour of ant colonies. Hence, the ACO uses an element of the ants' attributes to find the most optimal path to a food source. In nature, ants communicate through pheromones, which are a chemical left by members of their colony that helps to direct them to possible food sources (Dorigo *et al*., 2006). The stronger the pheromone, the shorter the path to the food source. The ACO algorithm emulates this foraging behaviour, where an ant represents a possible solution comprising a set of nodes visited by the ant in the path. Hence, when other ants want to choose the nodes, these ants will choose nodes with the highest level of pheromones.

Figure 3 shows the ants behaviour in four situations. In this example, the nest is located at one end and the food source is located at the other. As shown in (a), the ants leave the nest to search for food and return by moving randomly based on the pheromone trail. If there is an obstacle on the pheromone trail (b), the ants react immediately by searching for alternative paths around the obstacle, as in (c). In (d), the ants have found the shortest path to the food source (the path with the highest level of pheromones) This path is usually the most optimal solution.

Hence, with regards to adapting the ACO process to the LPM and reflecting the time segmentation of the TOU tariff formulation. The objective is to find the most optimal solution

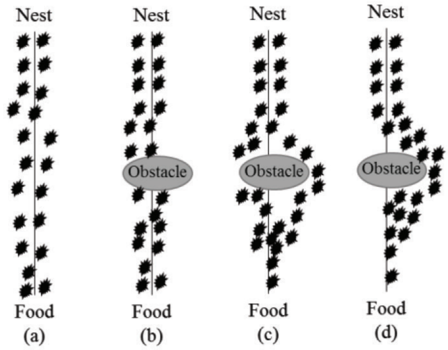

Figure 3: Behavior of ants in nature

for the reduction of electricity costs for the residential load profiles that represent residential power consumption behaviour.

Initialization

The ants represent a set of possible initial load profiles, *N*. The change in each electricity energy cost (called Cost) is represented as. The fitness values will be used to update and gather more ants to proceed to the next step. Equation 4 shows the initial condition of the load arrangement. Referring to works by Shweta and Singh (2013), Stodola *et al*. (2015), Wong and Komarudin (2008), the initial constant parameters of the ants were set as follows: $\alpha = 1$, $\beta = 0$, and $\rho = 0.3$.

$$N = [n_{x1}, n_{x2}, n \dots \dots \dots \dots \dots n_{xn}] \quad \textbf{(4)}$$

Generation of Ant and Calculation of the Transition Probability

The ants choose their solution (node) to the problem based on a probability rule. The ACO algorithm generates a new set of ants in each iteration according to the desired nodes. The probability of an ant selecting a specific node is represented by the Equation 5:

$$p(S_p) = \frac{r_{ij}^{\alpha} \times \eta_{ij}^{\beta}}{\Sigma \quad r_{ij}^{\alpha} \times \eta_{ij}^{\beta}} \quad \textbf{(5)}$$

where:

$p(S_p)$: Probability of Limit will be chosen in line with the partial solution

a_{ij} : Limit from Node to Node

r_{ij} : Pheromone values at

η_{ij} : Heuristic value, which is typically the inverse of the cost of going through

α : Pheromone importance factor

β : Heuristic importance factor

The ants start to explore their node by randomly selecting a starting point in each cycle of the system. The ants can only visit each node once. In the initial stage, the pheromone level is set as a low positive constant between any two nodes. The probability is calculated iteratively until the ants have reached all of the nodes, and the pheromone level is updated simultaneously. In this step, the fitness value is calculated by using the TOU_{min} formulation as in equation (2) subject to the constraint equation (3) to determine the Cost in the loop. The updated pheromone values are influenced by equation (2) and constraints in equation (3).

Updating Pheromones

Once the ant has evaluated its solution, and the corresponding fitness value has been calculated, the fitness value is used to update the pheromones, where the level of deposited pheromone has been identified. The increase of pheromone levels on the trail the ant continues to deposit will sharply limit the connecting nodes used by the ant. However, there is a possibility that the pheromone levels will decrease and this process is known as evaporation. The process of pheromone evaporation is updated according to the following equation:

$$r_{ij} = (1 - \rho) \text{ x } r_{ij} \quad \textbf{(6)}$$

where:

r_{ij} : Pheromone value at the limit from i to j
ρ : Pheromone evaporation factor

Likewise, the process of pheromone reinforcement is updated according to the following equation:

$$r_{ij} = r_{ij} + \sum \Delta r_{ij} \quad \textbf{(7)}$$

where:

r_{ij} : Pheromone value at the limit from i to j
$\sum \Delta r_{ij}$: Pheromone to be added to the trail by an ant, which is dependent on the length/ cost of the path taken by the ants.

After the pheromone levels have been updated, a counter is used to measure the maximum number of iterations. During the process, the ants move from one node to other nodes, and the transition probability is calculated accordingly.

Convergence

The pheromone levels are updated until the maximum iteration is reached, and the ants will take a similar trail. The optimal load profile reflecting minimum cost of the electricity is gained when the values of pheromone level have achieved maximum iteration. As for the ACO method presentation, when the criterion for the best Cost is fulfilled, Cost has converged. In this stage, the minimum electricity cost is obtained.

If the criterion for Cost is not fulfilled, a list of new possible optimum settings for the ants will be generated and the whole procedure is repeated based on Figure 4 accordingly.

Results and Analysis

This section presents analyses of the two rates of electricity tariff, which are flat baseline tariff and TOU tariff for residential. The TOU tariff rate for peak hours was adopted from the average of the existing block tariff, while for off-peak tariff rate was decided to remain the first price in the block baseline tariff rate. Meanwhile, baseline tariffs followed the existing Tenaga Nasional Berhad rate as published in (Energy Commission (Malaysia), 2019a).

For this study, the optimisation was tested by a different value of the weighted factors of the load shifting based on controlled and uncontrolled loads, which were *W*=5%, *W*=10%, *W*=15% and *W*=20%.

Figure 5 and Figure 6 show the best power consumption profile that was selected based on the higher savings earned. Based on this observation, the peak demand was transferred to the off-peak area which was 12:00 am to 1:00 am (~31kW). The loads have been shifted from the critical peak zone to the off-peak zone, which has a lower tariff rate compared with the baseline flat tariff. Consumers have taken the initiative to define the controlled for about 20% of their appliances as an example of general appliances such as washing machines, dishwashers, and air-conditioning.

Apart from that, the adoption of the ACO algorithm has initiated the best load profile arrangements for all cases, while increasing the controlled involvement in the weightage set was contributed to the upsurge in electricity cost savings.

Figure 7 demonstrates the iteration numbers of the fitness function for the ACO algorithm. After running of the simulation five times, the case of Data 5 was selected to be the best iteration which was 217. The stability of the ACO algorithm in obtaining this result was credible since the iteration results and fitness values were not much different. Two stages of the process flow in the ACO algorithm were able to support the stability of the results.

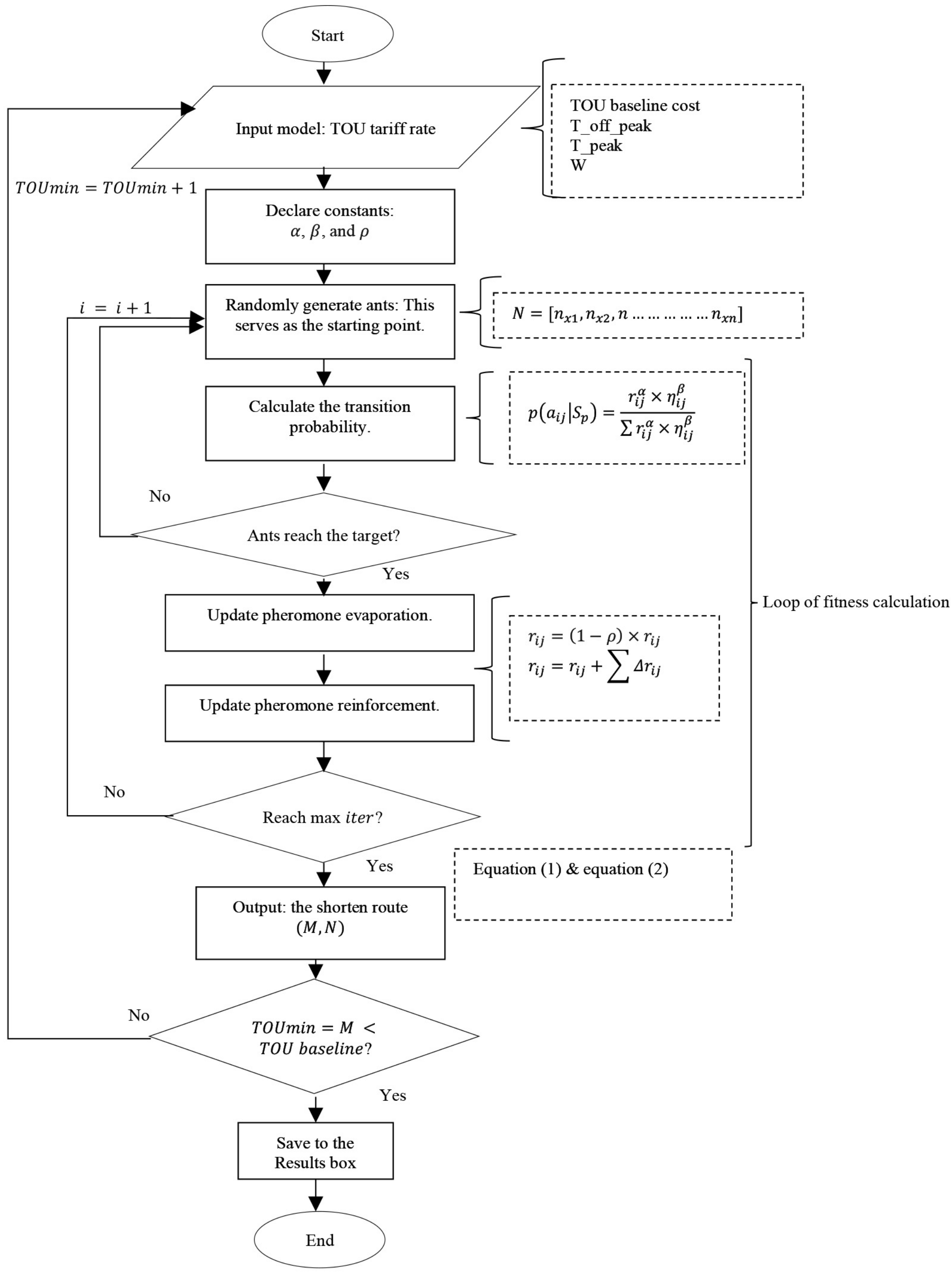

Figure 4: Steps involved in the ACO algorithm to minimize the electricity cost of residential consumers

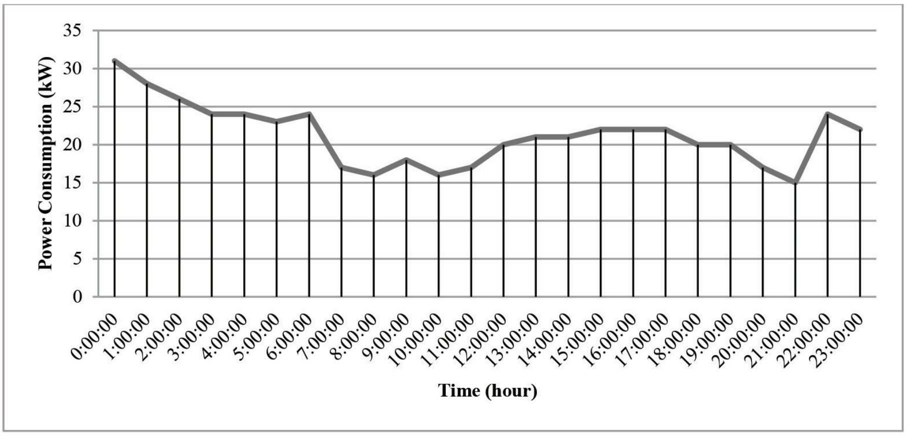

Figure 5: Best load profile after optimization

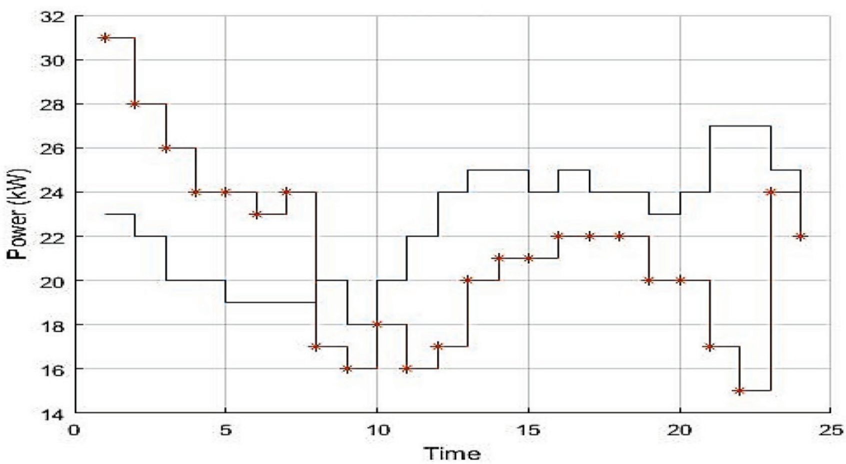

Figure 6: Comparison of the optimum power consumption profile to the baseline profile

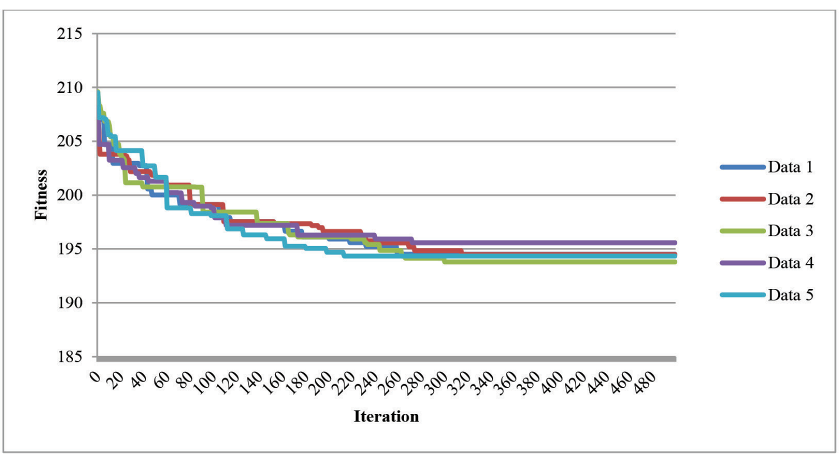

Figure 7: Simulation results of the five data for ACO algorithm

On the other hand, Figure 8 presents a comparison of the cases based on the weightage factor. The flat baseline tariff cost recorded monthly was ~MYR 211.45. It was observed that the total monthly electricity bill had reduced tremendously when the ACO algorithm was applied concurrently to the weightage setting. As presented in Table I, the saving in some cases was between ~7.29% and -8.35% with between 5% and 20% of the load shifting when the weightage was applied.

These results show that the TOU tariff with the encouragement of the LPM programme while promoting the policy for the DSM at the national level. Consumers gain the benefit from the monthly bill reduction while gaining experience and practice with LPM.

Utilities providers have the opportunity to promote better price signal policies for more efficient market stability where the cost of the peak demand in the generation side would sink accordingly.

Conclusion

In this study, optimal formulation for the load profile management is presented while the optimisation ACO algorithm has been adopted to determine the effectiveness of the demand response programme. An efficient load shifting strategy was applied to reflect the best proposed tariff structure for the residential consumer in the Malaysian electricity market.

For consumers satisfaction, the cost-savings on the monthly bill after load shifting proves the efficacy of the TOU tariff compared with the existing flat tariff. The LMP programme in applied in tandem with the demand response policy provides the consumers with more benefits while contributing to the power system markets stability on the generation side.

However, the inability of this study to get adequate details of the consumers' power consumption profile based on the residential home types would have to be improved in future studies.

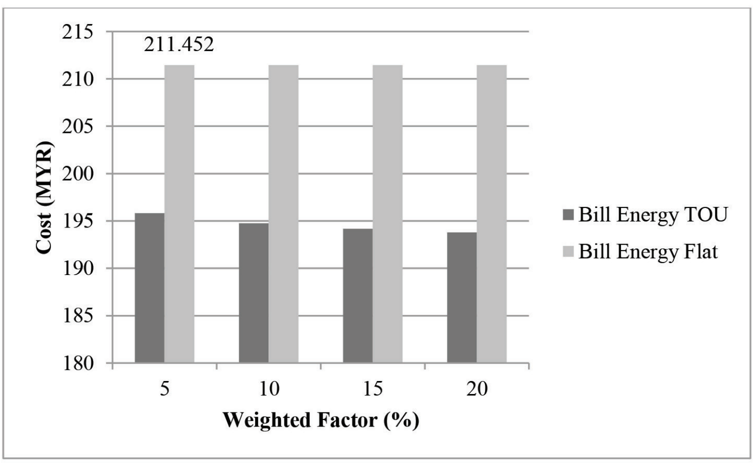

Figure 8: The comparison electricity cost and after the optimization between TOU and flat tariffs

Table 1: Total bill of the electricity for all cases with saving percentage

Case	Monthly Electricity Bill of TOU Residential (MYR)	Percentage Saving (%)
W=5%	195.8296	7.39
W=10%	194.741	7.90
W=15%	194.176	8.17
W=20%	193.7995	8.35

This study can be pushed further or continued by considering a specific LPM programme for the appliances' load in specific residential consumers home types. Furthermore, the other type of algorithms should be tested to enable a comparison and improve the performance of the load movement.

The management of the utility company and the government would benefit from this study as a reference for better residential tariff policies in the MESI 2.0. The preparation for the reform of the electricity market should consider the TOU tariff as the alternative for residential consumers to promote better policies for the DSM programme in Malaysia.

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