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Appropriateness of EToU electricity tariff program for industrial type consumers: an investigation of cost benefit

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ABSTRACT

In mitigating the peak demand, the energy authority in Malaysia has introduced the enhanced time of use (EToU). However, the number of participants joining the programs is less than expected. Due to that reason, this study investigated the investment benefit in terms of electricity cost reduction when consumers subscribe to the EToU tariff scheme. The significant consumers from industrial tariff types have been focused on where the load profiles were collected from the incoming providers' power stations. Meanwhile, ant colony optimization (ACO) and particle swarm optimization (PSO) are applied to optimize the load profiles reflecting EToU tariff prices. The proposed method had shown a reduction in electricity cost, and the most significant performance has been recorded congruently. For a maximum 30% load adjustment using ACO optimization, the electricity costs have been decreased by 10% (D type of tariff), 16% (E1 type of tariff), 9% (E2 kind of tariff), and 1.13% (E3 type of tariff) when compared to the existing conventional tariff. The cost-benefit of the EToU tariff switching has been identified where the simple payback period (SPP) is below one year for all the industrial types of consumers.

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1. INTRODUCTION

The increasing electricity demand contributes to energy generation to increase CO2 gas emissions. In recent data founding, it was reported that 84% of CO2 emissions are contributed by industrial/manufacturing activities [1], [2]. Since the coronavirus disease 2019 (COVID-19) pandemic promotes lockdown among energy consumers, CO2 emissions are reduced in line with the energy demand decreased from the industry sectors. However, the long-term and economic benefits in terms of demand-side management (DSM) should be considered so that future planning would consider the economic and financial aspects of many related consumers programs towards load management [3]. Thus, DSM programs should be introduced to reduce the impact of peak demand and the power system generation tension; the demand response program and energy efficiency for the post pandemic COVID-19 [4]. In 2022, there has been an upsurge in electricity peak demand in Malaysia since the colossal development and industrial process are restarted to operate where electricity tariff switching is available. Since 1995, the government has purposely implemented the time of use (ToU) tariff scheme to commercial and industrial consumers by promoting the load shifting where the energy price for off-peak hours is cheaper for about 20% compared to the flat tariff price. However, the ToU scheme has a maximum demand charge that is still high compared to the conventional flat tariff. Concerning the issue, Tenaga Nasional Berhad (TNB) has introduced a more advanced tariff, namely the enhanced time of used (EToU) tariff scheme, in 2016. The EToU tariff scheme offers a more flexible tariff time zone with three energy prices for peak, off-peak, and mid-peak and two prices for maximum demand in peak and mid-peak allocation. Nevertheless, it was reported that only 1% of the consumers joined the scheme. Meanwhile, the others refused to participate due to being less confident to apply the load management strategies [5]. It is also related to the provider's less promotion where the consumers have little knowledge of how to take load management action.

Since there, the researchers have investigated the issues and tried to help the consumers by proposing the techniques required to enjoy cost benefits from the EToU tariff scheme. As presented in [6], [7], industrial and commercial consumers' load profile was investigated to reflect the EToU tariff scheme compared to the ToU tariff. As for standard load shifting implementation, the consumers need to adjust the load for about ~30 to 70% to enjoy energy consumption cost reduction compared to flat and ToU tariff schemes. Since the application of the evolutionary algorithm is excellent in solving many complex problems, especially in power system study, Azman *et al*. [7] have promoted the evolutionary algorithm (EA) to find the optimum load profile for specific commercial consumers by adopting EToU tariff prices. The energy consumption cost was reduced at all six-segmentation zones of the peak, mid-peak, and off-peak when the load adjustment was put for about 50%. The optimum load management weightage differed depending on the consumers' load profile and the business activities dealing with the cost reduction under the EToU tariff scheme, as explained in [8]. The authors have adopted particle swarm optimization (PSO) to manage the simultaneous DSM strategies formulation (peak clipping, valley filling, and load shifting) to deal with six-segments of EToU tariff price.

In conjution to the DSM technique application to deal with ToU tariff design around the world, Rehman *et al*. [9] and Makroum *et al*. [10] has applied the load shifting from high-peak hours to low-peak hours concurrently with the adoption of optimization algorithms, namely bacterial foraging optimization (BFO) and genetic algorithm (GA). As the application of the optimization algorithm is superior results, analysis of the effect of ToU tariff and maximum demand on the power exchange of the power grid can be done strategically [11], [12]. Ultimately, in [13], the optimization algorithm and optimal DSM strategy formulation to reflect the EToU tariff scheme have been used to optimize the load profile to reduce the electricity price and maximum demand in peninsular Malaysia. Meanwhile, Shaari *et al.* [14] use EToU tariff and ToU tariff prices for a chiller plant operation to optimize the cost of the process. As the significant energy user in most commercial buildings, the chiller plant operation electricity cost optimization would benefit private consumers and government agencies.

In the EToU tariff scheme study, the optimization algorithm's application was less focused on past studies, mainly for implementing the optimal DSM strategy to the specific consumers. Meanwhile, the cost-benefit of the investment to switch the conventional tariff to EToU tariff has also less been presented in the area of study. Therefore, this study proposed an investigation of the cost-benefit under the EToU tariff scheme, which applies the ant colony optimization (ACO) and PSO algorithms while reflecting load management strategy under the demand response program in Malaysia. ACO algorithm is famously known to be a probabilistic algorithm used to find an approximately optimal solution through an ant colony-inspired process [15]. Artificial ants or simulation agents search for the most straightforward solution by moving through parameter space. The agents record their location and solutions that will later be spread to other agents to find the best solutions among all of the information gathered [16]. ACO is selected in this study because it performs a model-based search and is similar to estimating distribution algorithm [17]. In conjunction with that, the PSO introduced by Kennedy and Eberhart [18] will be the baseline performance algorithm to compare with ACO algorithm performance. Those comparisons purposely test the load profile from all categories under the industrial tariff offered by TNB in peninsular Malaysia. Since the simultaneously DSM strategies have been applied by previous studies for commercial buildings, investigating appropriateness to industrial consumers is essential to prove that the EToU tariff scheme could be used by massive segmentation of industrial consumers.

Hence, the paper's arrangement is considered as: section 2 presents the formulation and tariff structure methodology while covering the implementation of the PSO and ACO algorithms. Next, the simulation case study, results, and discussion are presented in section 3. Meanwhile, section 4 concludes the findings and recommendations for future research.

2. RESEARCH METHOD

2.1. Load management formulation

EToU tariff is in the pricing unit. The simulation aims to optimize the use of electricity and rearrange the load arrangement of the manufacturing's factory. The formulation was written in (1).

$$\Delta EToU_{eCost} + MD_{Optimum\ Cost} \tag{1}$$

$\Delta EToU_{eCost}$ is the electricity cost of wanted load cost after applying load management strategies in regards with the six-time segmentation of EToU and are written in (2). Meanwhile, $MD_{Optimum\ Cost}$ is the variable to $EToU_{Min\ Cost\ Saving.}$

$$\Delta EToU_{eCost} = \left(\sum_t^{N=10} \Delta P_{op} \times TP_{op}\right) + \left(\sum_t^{N=3} \Delta P_{mp1} \times TP_{mp}\right) + \left(\sum_t^{N=1} \Delta P_{p1} \times TP_p\right) + \left(\sum_t^{N=2} \Delta P_{mp2} \times TP_{mp}\right) + \left(\sum_t^{N=3} \Delta P_{p2} \times TP_p\right) + \left(\sum_t^{N=5} \Delta P_{mp3} \times TP_{mp}\right) \quad (2)$$

Where, ΔP_{op} is the changes of off-peak desired load curve with the time change of $N = 10$. ΔP_{mp1}, ΔP_{mp2}, ΔP_{mp3} Accordingly, the changes of the mid-peak desired load curve with the time change, $N = 3$, 2 and 5. ΔP_{p1} and ΔP_{p2} are the differences of peak desired load curve with time change $N = 1$ and $N = 3$ and TP_{op} is the EToU tariff rate for off-peak time zone, TP_{mp} is the EToU tariff rate for mid-peak time zone, TP_p is the EToU tariff rate for peak time zone. Meanwhile, t represents the time step for each segmentation of EToU block for peak, off-peak and mid-peak. The general equation for overall solutions of LSM strategies used in this study which is valley filling (VF), peak clipping (PC) and load shifting (LS) as written in (3).

$$\Delta P_{OP,MP1,P1,MP2,P2,MP3}^{General} = \sum_{ts,i}(\Delta P_{ts,i}^{VF} \times W_{VF}) + (\Delta P_{ts,i}^{PC} \times W_{PC}) + (\Delta P_{ts,i}^{LS} \times W_{LS}) \quad (3)$$

Where, $\Delta P_{ts,i}^{VF}$, $\Delta P_{ts,i}^{PC}$ and $\Delta P_{ts,i}^{LS}$ are the changing quantity of wanted load of VF, PC and LS strategies at random load (i) in time segmentation (ts) respectively. Random load setting selection (i) for its upper and lower bound is set as in (4) to reflect controlled apportionment accordingly.

$$0.005 \leq i \leq 0.30 \quad (4)$$

W_{VF}, W_{PC} and W_{LS} are the weightage of load apportioning of DSM strategies to be used in every single load profile generated. There are several constraints of DSM strategies that must be set up in this project which are:

1) VF constraints
$\Delta P_{ts,i}^{VF}$ is chosen during time segmentation with low quantity of base load price. The (ts) alteration of VF selection:

$$Average\ load\ price > \Delta P_{ts,i}^{VF} > Min\ baseload\ price \quad (5)$$

2) PC constraints
$\Delta P_{ts,i}^{PC}$ is chosen during two biggest price of time segmentation loads as well as where the location of the maximum demand where (ts) alteration:

$$Average\ load\ price > \Delta P_{ts,i}^{PC} > Max\ baseload\ price \quad (6)$$

3) LS constraint
After VF and PC selection have completed, LS is the last one, so that the rest of the segmentations will be performed by LS. The proposed LS procedure process is presented in (7), (8), and (9) accordingly.

$$\Delta P_{ts,i}^{LS} \cong \Delta Z_{ts,i}^{shift} \quad (7)$$

$$\Delta Z_{ts,i}^{shift\ down} = \left(\Delta Z_{up}^{shift} - \left(\left(\Delta Z_{up}^{shift} - \Delta Z_{down}^{shift}\right) \times \omega\right)\right) \quad (8)$$

$$\Delta Z_{ts,i}^{shift\ up} = \left(\Delta Z_{up}^{shift} - \left(\left(\Delta Z_{up}^{shift} + \Delta Z_{down}^{shift}\right) \times \omega\right)\right) \quad (9)$$

Where, ΔZ_{down}^{shift} is the load decrease changes at particular time segmentation (ts) for the load, i. ΔZ_{up}^{shift} is the load increase changes at particular time segmentation (ts) for the load, i. The ω is the weightage of load randomly decreasing and increasing at lower and upper bound load setting sets in (4).

4) Optimal maximum demand (MD) selection constraint
The MD selection respective to charge of MD is summarize in (10) and (11) meanwhile, the optimum MD charge obtained through selection of the combination both mid-peak and peak is shown in (12).

$$MD_{MP}^{cost} = Max[L_{T2}; L_{T4}; L_{T6}] \times MD_{MP}^{TP} \quad (10)$$

$$MD_{P}^{cost} = Max[L_{T3}; L_{T5}] \times MD_{P}^{TP} \quad (11)$$

$$MD_P^{cost} \geq MD_{Optimum}^{Cost} = MD_{MP}^{cost} \quad (12)$$

Where, MD_{MP}^{cost} is the ideal power load determination at mid-peak area and MD_P^{cost} is the ideal power load determination at peak area. The L_{TN} is the determined power load for number n at specific time segmentation (ts). Meanwhile, MD_{MP}^{TP} and MD_P^{TP} are the charge of *MD* during mid-peak and peak.

5) Total energy constraint
   Total energy before and after the optimization through the process of DSM strategies should not exceed ± 5%. In (13) is the constraints of six-time segmentation for total energy consumption (kWh) before and after optimization.

$$\sum E_T \cong \sum E'_T \quad (13)$$

6) Load factor index (LFI) written in (14) is used as verification for load profile improvement that is based on previous optimum formulation and constraints.

$$LFI = \frac{\sum E_{TSn}}{MD_{Optimum}^{kW} \times day \times t} \quad (14)$$

Where, $MD_{Optimum}^{kW}$ is the MD optimum selection in kW at peak or mid-peak zones, $\sum E_{TSn}$ is the total electricity consumption in kW for total n time segmentations, t is the electricity usage time. In this study, the ACO and PSO has been applied to find the total cost-benefit for the appropriate load profiles of several types of consumers from a variety of tariff under ToU scheme. The application of both algorithms is describing in the following sections.

2.2. Ant colony optimization

Ant colony optimization algorithm is an optimization technique used to solve problems through graphs. This optimization method is developed based on the behavior of a colony of ants. The paradigm used in this optimization is based on the communication of biological ants through pheromone-based communication [19], [20]. The ants travel in search of food and leave trails of pheromones and attract other ants to follow the trails, which is why ants always travel in a line. The more pheromones laid out on the path, more ants will follow the path, and that path will be the best solution to the problem faced. In the ACO algorithm, two processes are involved: generating the ants process and updating the pheromones process. A new set of ants will be generated in each iteration respective to the desired nodes in the first process. The probability of ant to select a node is expressed in (15).

$$p(\alpha_{ij}/S_p) = \frac{r_{ij}^{\alpha} \times \eta_{ij}^{\beta}}{\Sigma r_{ij}^{\alpha} \times \eta_{ij}^{\beta}} \quad (15)$$

Where, $p(\alpha_{ij}|S_p)$ is the probability that the limit α_{ij} will be selected in with the partial solution S_p, α_{ij} is the node i to node j limit. The r_{ij} is the α_{ij} pheromone values. The η_{ij} is a heuristic value, or the inverse of the cost of going through limit α_{ij}. Meanwhile, α is the importance factor of pheromone and β is the importance factor of heuristic.

After the trails have been updated after the ants have completed their solution, updating pheromone process will start. In this process, the level of shifted pheromone is determined. The escalating value of pheromone in trails leave by ants will restrain the connecting nodes it has used. There are also cases of decreasing pheromone level due to evaporation process. In (16) and (17) presents the process of updating pheromone evaporation and reinforcement accordingly.

$$r_{ij} = (1-\rho) \times r_{ij} \quad (16)$$

Where, r_{ij} is the value pheromone at the limit ranging from *i* to *j*. ρ is the pheromone evaporation factor

$$r_{ij} = r_{ij} + \sum \Delta r_{ij} \quad (17)$$

Where $\sum \Delta r_{ij}$ is the pheromone that will be added by an ant to the trail, that rely on the length of the trail that used by the ants. There four steps for ACO algorithm that has been applied to this study are:

– Step 1: ants are initialized by setting $\alpha = 1, \beta = 0$ and $\rho = 0.3$ referred to [21], [22]and [23]. The ants expressing a possible initial load profile set to identify each electricity energy cost change or the algorithm are called nodes in 24-hour time. In the next step, the fitness values obtained is used.

- Step 2: the constraints is formulated, and the cost is identified. The pheromone values that have been updated will be engaged in the EToU formulation in form of MD cost and the DSM strategy as in (2) until (12) accordingly. The best cost value in the first process in ACO is chosen from the latest update of total electricity cost in six-time segmentation. The second process of finding the updated ants' pheromones will start after the first process of ACO is done.
- Step 3: the best cost value obtained during updating the pheromones are used to determine the best total energy cost covering all segmentations, while the ideal load profile represented by the best ants is developed. Once again, (16) and (17) are applied in this step.
- Step 4: after the requirements for the best cost have been achieved, to satisfy the constraints, the achieved value of cost is concluded to be convergence value. If the condition is not yet fulfilled, the process will begin all over again to find the new possible setting of ants list. In this step, the contribution of electricity energy cost and MD cost to the assistance of LFI is generated.

2.3. Particle swarm optimization

PSO is a method that optimizes a problem by repeatedly trying to improve already existing candidate solutions. This optimization algorithm is inflicted by animal movement such as a colony of bats and school of fish [24], [25]. PSO algorithm solves the problem by letting a swarm of particles moves freely inside the search space to search for the best position. Each particle updated its best positions found in the space attracting other particles, thus generating a swarm of particles. The equation used to find the updated particle's velocity and position is (18) and (19), respectively.

$$V_j^{k+1} = \left(\omega \times V_j^k\right) + \left(C_1 r_1 \left(P_{bestj}^k - X_j^k\right)\right) + \left(C_2 r_2 \left(G_{bestj}^k - X_j^k\right)\right) \tag{18}$$

$$X_j^{k+1} = X_j^k + V_j^{k+1} \tag{19}$$

Where, V_j^k is the particle j velocity in k iteration, X_j^k is the particle j position in k iteration, and ω is the inertia weightage. Meanwhile, P_{bestj}^k is the fitness function best value that has been obtained by particle j in k iteration, and G_{bestj}^k is the best value between the fitness values, The C_1 and C_2 are the constants that presenting weightage factor of random acceleration terms, V_j^{k+1} is the updated velocity, and X_j^{k+1} is the updated position.
The steps used by PSO algorithm in this study to determine the optimal electricity cost is:

- Step 1: population is initialized using daily load profile based 24-hour to represent consumers' power consumption shape. A random generator in the program produces the variables throughout the system to evaluate the electricity usage cost for the load profile in the next step. PSO parameters like number of particles N, weighting factor, C_1 and C_2, and maximum number of iterations are initialized. 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. Optimization is conserves and all constraints in (2) until (14) are applied to achieve the ideal electricity usage cost.
- Step 2: calculation of fitness. An initial population of particles that have random positions and velocities are generated randomly. The load profile will be analyzed, the total EToU electricity energy cost and MD cost is calculated with (2) by using correlation from the (3), (4) and (12) at once for each particle that satisfy the constraints in step 1. Meanwhile, the input of calculation and constraints are used to calculate LFI referred to (14).
- Step 3: determination of P_{best} and G_{best}. During the exploring phase, the two finest values are listed. The values recorded are correlated with the best solution that has been widen so far by each particle that maintain the path of its position in the space. P_{best} and G_{best} presenting the generation of finest EToU energy consumption expenses which also has contributed to generate optimum MD cost.
- Step 4: updating velocity and position. The particles' velocity and position are updated by applying (18) and (19) accordingly. The new particle's velocity represents a load profile curve change. For the time being, the new particle's position used to evaluate the total load profile in all segmentations. If the convergences will occur with this new position set and if the convergence is not fulfilled, the process will repeat all over again.

3. RESULTS AND DISCUSSION

3.1. Case study

The arrangement of the case study that has been set for this project is as:

- Case 1: baseline of the flat/ToU tariff rates.
- Case 2: EToU tariff rate energy consumption without DSM strategies and without optimization algorithms.
- Case 3: EToU tariff rate energy consumption without DSM strategies and using optimization algorithms.

– Case 4: EToU tariff rate energy consumption using 10% of the DSM strategies and optimization algorithms.
– Case 5: EToU tariff rate energy consumption using 20% of the DSM strategies and optimization algorithms.
– Case 6: EToU tariff rate energy consumption using 30% of the DSM strategies and optimization algorithms. Industrial D (consumers with low voltage 415 V with flat tariff) and E1 (consumers with medium voltage 11/33 kV with flat tariff) load profiles as the baseline; meanwhile, Industrial E2 (consumers with medium voltage 11/33 kV with ToU tariff) and E3 (consumers with high voltage 132 kV with ToU tariff) load profiles as the baseline. In addition, the load weightage of DSM strategies has been set to 10%, 20%, and 30% as the load management weightage.

3.2. Analysis of load profile using ACO algorithm

The output simulation of energy power consumption for all six cases using ACO is shown in Figure 1 accordingly. Figure 1(a) shows that after implementing DSM strategies and the ACO algorithm, the power consumption of all four load profiles for 24-hours operation decreased. The power consumption can be seen falling the most at case 6 for both medium voltage consumers E1 and E2 as shown in Figure 1(b) and Figure 1(c), respectively. This is because most of the usage during peak hours and mid-peak hours from 8:00 am until 21:00 pm has been reduced, which means it has been shifted to off peak hours from 10:00 pm until 7:00 am.

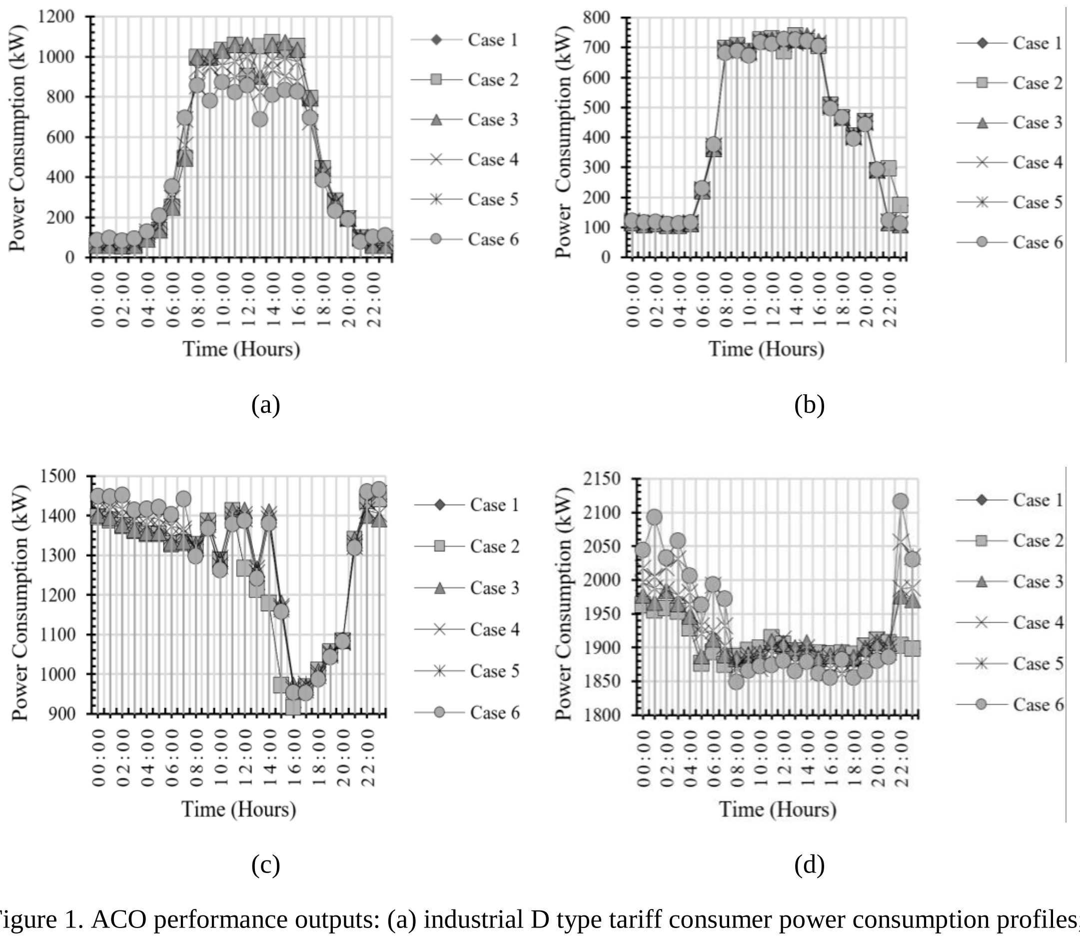

Figure 1. ACO performance outputs: (a) industrial D type tariff consumer power consumption profiles; (b) industrial E1 type tariff consumer power consumption profiles; (c) industrial E2 type tariff consumer power consumption profiles; and (d) industrial E3 type tariff consumer power consumption profiles

The results shown that ACO algorithm with the help of load management strategies has able to reduce the energy consumptions during peak hours. It reflects the load management strategies applied: load clipping, valley filling, and load shifting. From the Figure 1(d), it can be observed that the load shifting, and peak clipping strategies have successfully decreased the electricity power consumption during the peak time. However, meanwhile in off-peak and mid-peak, the power consumption increases due to load shifting and valley filling impact. It has shown that DSM strategies applied are efficient and industrial customers especially E3 tariff type can indeed manage their load using this weightage adjustment method.

3.3. Analysis of load profile using PSO algorithm

The output simulation of energy power consumption for all six cases using the PSO algorithm is shown in Figure 2. In Figure 2(a), after implementing DSM strategies and PSO algorithm, the power consumption for 24-hours operation was also decreasing same as ACO power consumption outputs. Industrial D tariff power consumptions not only decreasing during peak hours but for overall 24-hours. PSO algorithms are more effective in reducing the energy consumptions for medium voltage of consumers E1 and E2 industrials tariff in the peak zones as illustrated by Figure 2(b) and Figure 2(c) accordingly. Meanwhile, Figure 2(d) shows the differences between the baseline of case 1 to the 30% weight arrangement of case 6 are significant for high voltage consumers (E3).

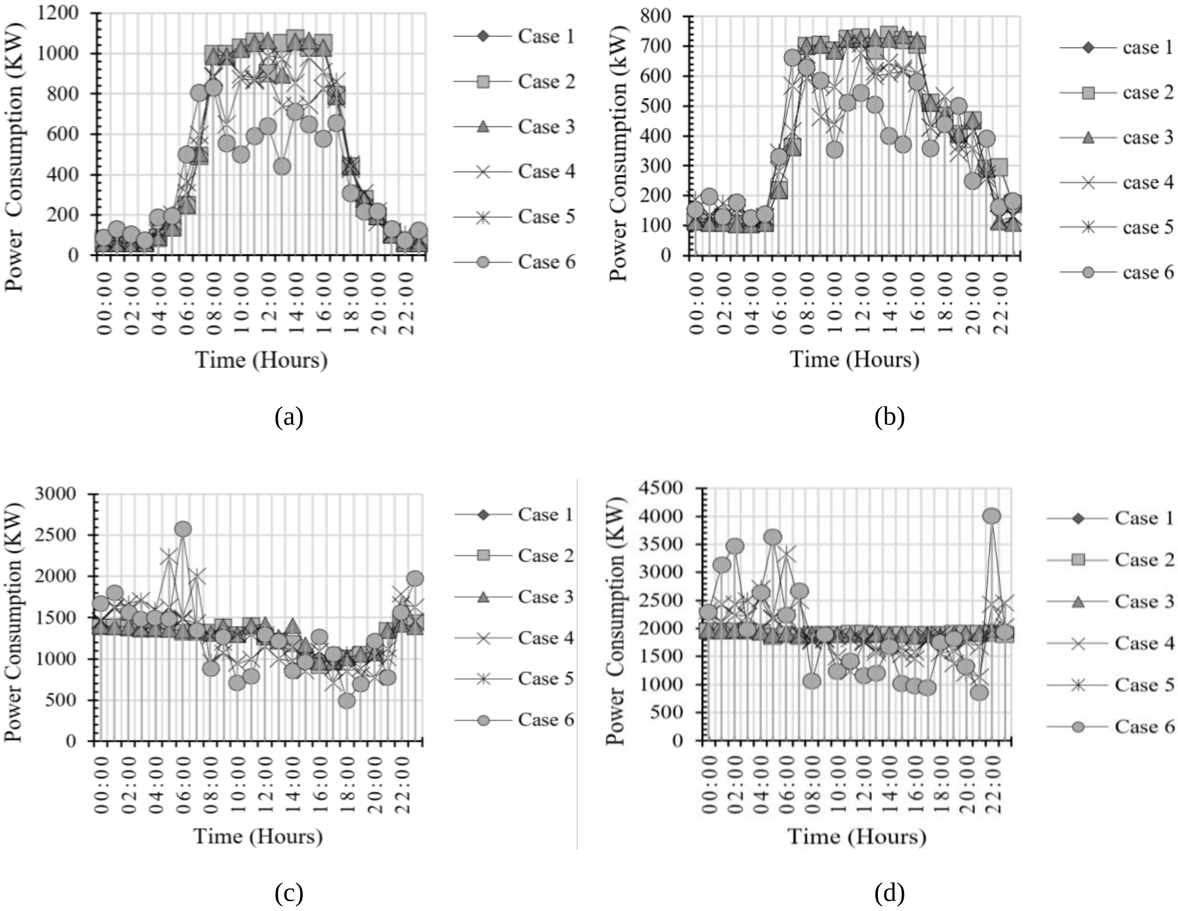

Figure 2. PSO performance outputs: (a) industrial D type tariff consumer power consumption profiles; (b) industrial E1 type tariff consumer power consumption profiles; (c) industrial E2 type tariff consumer power consumption profiles; and (d) industrial E3 type tariff consumer power consumption profiles

3.4. Comparison of optimum performance

Table 1 presents the optimization output performance for industrial D data. From the table, after the ACO optimization and 30% load adjustment, the energy consumption decreasing by 12%, the total cost decreasing by 19% and the maximum demand was shifted to mid-peak. Meanwhile, for PSO algorithm, the energy consumption have been reducing by 26%, the total cost decreasing by 40% and the MD also has been shifted to mid-peak. From the analysis, PSO has shown better performance in reducing energy consumption. Table 2 presents the optimization output performance for industrial E1 data. From the table, after the ACO optimization and 30% load adjustment, the energy consumption decreasing by 2%, the total cost decreasing by 16% and the maximum demand was shifted to mid-peak. Meanwhile, for the PSO algorithm, the energy consumption has been decreasing by 15%, the total cost decreasing by 47%, and the MD has also been shifted to mid-peak. It can be concluded that for the industrial E1 load profile, PSO algorithm has better performance in reducing the energy consumption and the overall energy cost.

Table 3 presents the optimization output performance for industrial E2 data. From the table, after the optimizations of both algorithms with 30% load adjustment, there is an increment in energy consumption.

Still, the increment does not exceed the total energy constraint as mentioned earlier, which is ± 5%. Although there are increments in the total energy consumption, the total electricity cost for ACO and PSO algorithms decreases by 9% and 15%, respectively. Thus, the PSO algorithm reduces the total electricity cost than the ACO algorithm for the E2 load profile. Table 4 presents the optimization output performance for industrial E3 data. From the table, after the optimizations of both algorithms with 30% load adjustment, there is an increment in energy consumption. Still, the increment does not exceed the total energy constraint as mentioned earlier, which is ± 5%. Therefore, although there are increments in the total energy consumption, the total electricity cost for ACO and PSO algorithms decreases by 1.13% and 3%, respectively.

Table 1. Industrial D type of electricity tariff output performance for ACO and PSO algorithms

Industrial D tariff	ToU	Normal EToU	EToU after ACO optimization	EToU after PSO optimization
Energy consumptions (kWh)	12,336	12,336	10,880	9,295
MD (kW)	1,072	1,072	872	835
MD location	Peak	Peak	Mid-peak	Mid-peak
Energy consumption cost (RM)	4,157	4,592	3,921.41	3,259.07
MD cost	0	45,131	32,438.40	31,062
Total electricity cost (RM)	4,157	40,539	36,359.81	34,321.07
Normalized total electricity cost (RM)	4,157	40,539	32,723.83	24,024.75

Table 2. Industrial E1 type of electricity tariff output performance for ACO and PSO algorithms

Industrial E1 tariff	ToU	Normal EToU	EToU after ACO optimization	EToU after PSO optimization
Energy consumptions (kWh)	10,231	10,231	9,983	8,680
MD (kW)	740	740	727	631
MD location	Peak	Peak	Mid-peak	Mid-peak
Energy consumption cost (RM)	3,447.78	3,895.66	3,827.10	3,080.89
MD cost	21,904	26,270	21,519.20	18,678
Total electricity cost (RM)	25,352	30,165.70	25,346.30	21,759
Normalized total electricity cost (RM)	25,352	30,165.70	25,346.30	15,884.07

Table 3. Industrial E2 type of electricity tariff output performance for ACO and PSO algorithms

Industrial E2 tariff	ToU	Normal EToU	EToU after ACO optimization	EToU after PSO optimization
Energy consumptions (kWh)	30,181	30,181	31,178	30,448
MD (kW)	1,412	1,412	1,387	1,302
MD location	Peak	Peak	Mid-peak	Mid-peak
Energy consumption cost (RM)	8,842.63	9,629.78	9,993.60	9,195.73
MD cost	52,244	56,480	49,932	46,872
Total electricity cost (RM)	61,086.63	66,109.78	59,925.60	56,067.73

Table 4. Industrial E3 type of electricity tariff output performance for ACO and PSO algorithms

Industrial E3 tariff	ToU	Normal EToU	EToU after ACO optimization	EToU after PSO optimization
Energy consumptions (kWh)	45,773	45,773	46,478	46,294
MD (kW)	1,914	1,914	1,886	1,879
MD location	Peak	Mid-peak	Mid-peak	Mid-peak
Energy consumption cost (RM)	12,833	14,457	15,863.17	12,906.55
MD cost	67,947	66,990	72,463.60	65,765
Total electricity cost (RM)	80,780	81,447	80,529.84	78,671.55

3.5. Cost-benefit

The process to change from the previous tariff to the EToU tariff involved some investments. Table 5 shows the items that need to be paid by customers who wish to switch to EToU tariff, including the recharge job order (RJO) by TNB, sub-meters installation, energy monitoring system controller, and the display unit. The price in the tables is referred from TNB and energy monitoring traders in Peninsular Malaysia excluding goods and 6% service tax. The total investments after summing all of the item costs are MYR 56,600. To know whether the investments made by the customers to change from previous tariff to EToU tariff is worth it, two calculations can be done: simple payback period and internal rate of return.

Table 6 presents the simple payback period calculated for E1, E2, and E3 load profiles. Industrial D load profile is not considered because the analysis done before shows that industrial D should use the flat tariff to enjoy more savings. From the table, industrial E3 has the most prolonged payback period due to the enormous cost of electricity bills. Nevertheless, the payback period for all industrial load profiles is less than one year, which means customers will get back their investment in less than one year.

Table 5. Investment cost for the tariff transformation

Item	Price (MYR)	Unit	Total Price (MYR)
Recharge job order by TNB	12,000.00	1	12,000.00
Installation sub-meters	2,500.00	3	7,500.00
Controller for the energy monitoring system	8,500.00	3	25,500.00
Display unit (including installation)	5,800.00	2	11,600.00
Total Investment (MYR)			56,600.00

Table 6. Cost analysis for 3 types of tariff under industrial consumers

Item	Amount		
	E1	E2	E3
Annual energy cost (RM/year)	6,642,224.00	16,004,697.58	21,164,360.00
Annual energy cost saving (RM/year)	941,366.00	1,288,751.80	552,414.42
Investments cost (RM)	56,600.00	56,600.00	56,600.00
Payback period (year)	0.06	0.04	0.10

4. CONCLUSION

The electricity cost has been successfully reduced by applying the simultaneous demand side strategies and implementing the optimization of ACO and PSO algorithms. The proposed simultaneous DSM strategies have shifted the peak usage of industrial D, E1, E2, and E3 load profiles to off-peak zones based on the six-segmentation of EToU electricity tariff. The valley filling strategies have changed the load profile load curve by filling in the off-peak zones. The load clipping and load shifting have successfully reduced the peak consumptions and shift them to off-peak zones. As a result, the maximum demand in the baseline cases has been shifted to mid-peak zones, contributing to the decrease in electricity bill cost. Other than that, the performance of optimization algorithms, ACO, and PSO has been analyzed, and the ability to handle the energy load profile makes it easier for the optimization process. PSO algorithms were found more efficient in reducing the price of electricity while using the EToU tariff rates. From the analysis, the D tariff users should remain using the flatt tariff as the electricity usage and price are cheaper. Meanwhile, for E1, E2 and E3, they should change to EToU tariff. But the users need to carefully manage their load profile to utilize the benefits from EToU tariff fully. As for future research recommendations, the study would be extended to define the available load that could contribute to the more specific load management strategies.

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