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INVESTIGATION OF OPTIMAL OFF-PEAK TARIFF RIDER (OPTR) BY USING PARTICLE SWARM OPTIMIZATION FOR SELECTED COMMERCIAL AND INDUSTRIAL CONSUMERS IN MALAYSIA

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Abstract— In Peninsular Malaysia, Off-Peak Tariff Rider (OPTR) is offered to all medium voltage commercial and industrial consumers who are currently not enjoying any off-peak usage tariff rates. In this program, the consumers are able to obtain a discount rate of 20% with the condition that the load factor must be more significant than the average baseline set. Nevertheless, not all consumers are willing to commit. In this paper, a superior bio-inspired algorithm, Particle Swarm Optimization (PSO), is used to optimize the industrial and commercial load profile while adapting the simultaneous demand-side management (DSM) strategies such as peak clipping, valley filling, and load shifting. The

Particle Swarm Optimization	proposed combination technique has shown a reduction of electricity cost and an improvement of load factor for all optimal cases from the forecasting result when the different percentages of DSM strategies are applied accordingly. Hopefully, the findings of this study will help consumers to manage their energy consumption wisely and obtain the full benefit from the DR program.

I. Introduction

Globally, energy transition trends have drawn tremendous momentum, paving new paths toward energy sector reform in response to rising concerns about climate change and environmental sustainability to reduce energy-related greenhouse gas (GHG) emissions. Electricity generation accounts for the largest share of Malaysia's GHG emissions. As a developing country, rising energy demand has pressured the government to select cheaper sources of energy for power generation [1]. Previously, the maximum demand for the Peninsular Malaysia grid system increased by 3% in 2018 compared to 2017, with the highest maximum demand observed on 15 August 2018 being 18,338MW [2]. The industrial sector has contributed the highest demand, which is 48.8%, followed by the commercial sector, 29.8%, and residential, 20.7 % of the overall demand in Malaysia [3].

Consequently, a massive investment in the infrastructure is needed to meet the rising electricity demand in the country due to aging components of the power system that will have to be replaced. Therefore, the practices focused on balancing the electricity supply and demand have to be considered critically, such as Demand Side Management (DSM). DSM is the practice of planning, installation, and monitoring by the electricity utility that can impact energy use by changing the consumption patterns of consumers to achieve the necessary changes in load shape [4].

The primary objective of DSM is to encourage consumers to minimize peak-period electricity usage or relocate energy use from peak to off-peak hours to lower the load curve [5]. It can benefit the consumers and improve the reliability of the power system simultaneously. The demand response (DR) program under DSM has different tariff initiatives such as Time of Use (TOU), Enhance Time of Use (ETOU), and Off-Peak Tariff Rider (OPTR), which are offered to a large number of commercial and industrial consumers. DR is an effective tool for managing energy demand in order to ensure efficiency, stability, and resiliency at district-level [6]. The program's primary purpose is to reduce peak demand and promote independent load management actively. Since the electricity saved is more valuable than the electricity generated [7].

The electricity utility in Malaysia called TNB has designed a TOU tariff with two different time allocations: peak hour (8:00 AM – 10:00 PM) and off-peak hour (10:00 PM – 8:00 AM), where the energy pricing during off-peak is lower compared to peak hours [8]. Therefore, both consumers and utility can benefit from the price signal in TOU tariffs when consumers can shift the electricity consumption to lower-priced hours such as bill savings opportunities and related potential reduction in the cost of the whole power system [9]. Moreover, DR activities can contribute significantly to lowering the peak load in non-residential buildings. This improves power grid efficiency and reduces costly energy and peak demand charges [10].

The case study of the commercial building conducted in [11] has proven that appropriate load management can help the consumers reduce the electricity cost by the 20% discount rate during off-peak hours offered under OPTR tariff through the load factor improvement. The optimization of the operation schedule for the air compressor network integrated with TOU and ETOU tariff pricing is presented in [12]. Considerable cost saving is obtained due to extensive off-peak periods during the weekend and night-time. Whereas Ref [13] studied the scheduling problem for a flexible flow shop in the environment of TOU. Transferring the production activity from peak hour to off-peak or mid-peak hour is able to minimize the electricity cost while fulfilling customers' satisfaction and obtaining economic benefits.

However, the studies on ETOU tariff conducted in [14]–[16] show that without an appropriate DSM strategy such as load shifting will result in a higher electricity bill when the consumers change to the ETOU tariff from the conventional tariff immediately. Thus, a concrete strategy needs to be implemented to manage the load consumption effectively and gain benefits from the DR program.

At present, the implementation of Artificial Intelligence (AI) has gained relevance as a powerful technology for facilitating demand-side response to solve the high difficulty of the issues concerned with DR. In this scope, heuristic optimization is able to search for a near-optimal solution in a short period easily compared to other mathematical techniques [17].

For instance, Particle Swarm Optimization (PSO) [18], Ant Colony Optimization [19], [20], Evolutionary Algorithm (EA) [21], Evolutionary Particle Swarm Optimization (EPSO) [22], Pigeon Inspired Optimization (PIO) and Enhanced Differential Evolution (EDE) [23], Time-Constraint Genetic- Moth Flame Optimization (TG-MFO) [24] and Day-Ahead Grey Wolf Modified Enhanced Differential Evolution (DA-GmEDE) [25] are used to enhance the implementation of DSM strategies and solved the cost optimization problem which the results are summarized in Table 1.

Table 1: Cost comparison of PSO with other AI methods

Ref	Method	Total electricity cost reduction (%)
[18]	PSO & ACO	6.14% & 7.07%
[19]	ACO	2.1%
[20]	ACO	8.35%
[21]	EA	12.1%
[22]	EPSO	16%
[23]	PIO & EDE	10%
[24]	TG-MFO	32.25%
[25]	DA-GmEDE	23.9%

In this study, the simultaneous DSM strategies and mathematical formulation are presented and engaged to the bio-inspired algorithm, PSO, to obtain the electricity cost reduction and load factor improvement under the TOU-OPTR tariff. The case study involved an accurate load profile of commercial C1 and Industrial E1 consumers to be analyzed and compared according to the different DSM weights applied.

The rest of this paper contains section II, which demonstrates the formulation of the OPTR tariff and implementation of the algorithm. Section III presents the results and discussion. Lastly, section IV concluded the overall finding of this study.

II. Methodology

A. Formulation of OPTR Tariff

The formulation of OPTR tariff is stated in Equation (1)-(6) accordingly [11]. The equation (1) written below is the electricity cost (MYR) for OPTR in a flat tariff scheme

$$Flatt_{cost}^{OPTR} = Optimal_{eCost} + MD_{Optimum\ allocation}^{cost} \quad (1)$$

Where $Optimal_{eCost}$ is the cost for the electricity consumption of the optimal load curve after the implementation of DSM strategies considering the base price of the two time periods as proposed in Equation (2) below:

$$Optimal_{eCost} := min \sum_{hour\ i=1}^{N} P_{total\ \ consumption} \times \mathrm{TP}_{\mathrm{OPTR\ \&\ Flatt}}$$

$$= \left(\sum_{hour\ i=1}^{7} P_{op} \times TP_{OPTR}\right) + \left(\sum_{hour\ i=1}^{14} P_p \times TP_p\right) \quad (2)$$

where:
N = Total number of loads
P_{op} = Optimum power consumption in the off-peak period (desired load curve) concerning $hour\ i = 1$,
P_p = Optimum power consumption in the peak period concerning $hour\ i = 1$,
TP_{OPTR} = Tariff price for off-peak period set followed standard OPTR scheme discount set by the utility
TP_p = Flat tariff price for peak period set by the utility

Equation (3) is used to calculate the MD charge, the significant parameter in calculating the total electricity cost. Equation (1) indicated that $MD_{Optimum}^{cost}$ was set as the variable for $Flatt_{cost}^{OPTR}$. Thus, it is crucial to allocate the peak demand in a suitable allocation. Meanwhile, Equation (4) presented the optimum MD charge achieved by sorting the MD charges outside the typical distribution of MD.

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

$$= MD_{Optimum}^{Cost} < MD_P^{Cost\ current},\ MD_P^{cost\ reduction} \in MD_{Optimum}^{cost} \quad (4)$$

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 Load Factor Index (LFI) was used as the indicator to sustain the OPTR tariff scheme as given by Equation (5).

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

where:
$\sum E_{TSn}$ = Total electricity consumption for n time segments
t = time of electricity usage
$MD_{Optimum}^{kW}$ = Optimal selected MD in kilowatts (kW) in the peak or mid-peak time segment

The constraints for total energy consumption in kilowatt-hours (kWh) before and after the optimization together with DSM techniques should be equal or less than ±10% which is given by Equation (6):

$$\sum E_T \approx \sum E'_T \tag{6}$$

B. Constraints for DSM Strategies

The DSM strategies proposed in this project are valley filling (VF), load shifting (LS) and peak clipping (PC) [26]. The VF, LS, and PC focus on the demand response; thus, the general equation is written in Equation (7).

$$\Delta P^{General}_{OP,MD1,P1,MP2,P2,MP3} = \sum_{ts,i}(\Delta P^{VF}_{ts,i} \times W_{VF}) + (\Delta P^{PC}_{ts,i} \times W_{PC}) + (\Delta P^{LS}_{ts,i} \times W_{LS}) \tag{7}$$

Given the required load of VF, LS and PC strategies have the changing quantity which are $\Delta P^{VF}_{ts,i}$, $\Delta P^{PC}_{ts,i}$ and $\Delta P^{LS}_{ts,i}$ at random load (i) in time segmentation *(ts)* respectively. The upper and lower bound set for the random load selection *(i)* is written in (8) reflecting the controlled apportionment accordingly.

$$0.005 \leq i \leq 0.10 \tag{8}$$

W_{VF} , W_{LS} and W_{PC} are the weightages of DSM strategies which strategically applied in each load profile obtained where the constraints of the strategy are set below:

(i) VF constraints

$\Delta P^{VF}_{ts,i}$ is chosen during time segmentation with a low quantity of base load price. The *(ts)* alteration of VF selection must follow:

$$Average\ load > \Delta P^{VF}_{ts,i} \geq Min\ baseload \tag{9}$$

(ii) PC constraints

$\Delta P^{PC}_{ts,i}$ is selected during the two highest prices of *(ts)* loads and also the location of maximum demand where (*ts*) alteration follow:

$$Average\ load < \Delta P^{PC}_{ts,i} \leq Max\ baseload \tag{10}$$

iii) LS constraints

The proposed technique for LS is shown in Equation (11), (12) and (13) respectively:

$$\Delta P_{ts,i}^{LS} \cong \Delta Z_{ts,i}^{shift} \quad (11)$$

$$\Delta Z_{ts,i}^{shift\ down} = (\Delta Z_{up}^{shift} - \left(\begin{array}{c} (\Delta Z_{up}^{shift} - \Delta Z_{down}^{shift}) \\ \times\ \omega) \end{array} \right) \quad (12)$$

$$\Delta Z_{ts,i}^{shift\ up} = (\Delta Z_{up}^{shift} - \left(\begin{array}{c} (\Delta Z_{up}^{shift} + \Delta Z_{down}^{shift}) \\ \times\ \omega) \end{array} \right) \quad (13)$$

Given,

ΔZ_{down}^{shift} = load decrease changes at particular time segmentation (*ts*) for the load *(i)*

ΔZ_{up}^{shift} = load increase changes at particular time segmentation *(ts*) for the load, *(i)*

ω = weightage of load increases and decreases randomly at lower and upper bound load settings (8).

C. Particle Swarm Optimization Implementation

PSO was inspired by the schooling behaviour of birds and fish. To update the velocity and position, each particle learns from its personal historical best position, P_{best} and global best position, G_{best} found by the entire population. The updating equation of the *i*-th particle is stated as below [14].

Particle Velocity update:

$$V_j^{k+1} = (\omega \times V_j^k) + (C_1.r_1(P_{best,j}^k - X_j^k)) + (C_2.r_2\ (G_{best,j}^k - X_j^k)) \quad (14)$$

Particle Position update:

$$X_j^{k+1} = X_j^k + V_j^{k+1} \quad (15)$$

where:
V_j^k = particle j velocity in k -th iteration
X_j^k = particle j position in iteration k-th iteration
r_1 and r_2 = uniformly distributed random numbers in the interval [0,1]
ω = inertia weight
C_1 and C_2 = constants that defined weightage factor of random acceleration terms
$P_{best,j}^k$ = best value of fitness function obtained by particle j in k -th iteration
$G_{best,j}^k$ = best value among the fitness value

The following is the stage of application of the PSO algorithm in finding the optimum electricity energy cost:

Initialization**:** The process begins with the initialization of the population, which is determined by calling the daily load profile in 24-hours and the current energy consumption pattern of the consumers. In the following step, the system generates those variables using a random generator available in the program to compute the electricity cost for the profile. Next, the PSO variables are initialized, such as the number of particles N, weighting factors C1 and C2, and a maximum number of iterations. Optimization is sustained to ensure the effectiveness of energy costs, and all the constraints listed from (4) until (13) are purposefully applied.

Fitness Calculation**:** An initial population of particles with random positions and velocities is generated in the solution space. The load profile for each particle that meets the constraints as defined in the initialization stage is analyzed, and the total OPTR energy cost is calculated using Equation (1) and the correlation from Equation (2) and Equation (7) at the same time. Meanwhile, the calculation and constraint inputs are used to calculate LFI as written in Equation (5).

Determine P_{best} and G_{best} **:** During the search, the two best values are updated and saved. These values correspond to the best solution extended thus far by each particle that maintains the path of its coordinate in the solution space. It is denoted as P_{best}, and another best value is G_{best}, which is the overall best value achieved by any particle thus far. The P_{best} and G_{best} represent the best energy cost for OPTR also LFI generation.

New Velocity and Position**:** The velocity and position of the particles are updated in this process by using Equation (14) and (15), respectively. The particle's velocity represents an adjusting load profile curve. Meanwhile, the total load profile in all segments is evaluated using the new position.

Convergence Test**:** The convergence criterion was set as follows:

$ft\_max - ft\_min \leq 0.0001$

III. Results and Discussion

The test study was conducted by taking the real load profile of a university from C1 commercial consumer and load profile of a poultry manufacturing from E1 industrial consumer to analyze the effectiveness of OPTR formulation and performance of the PSO algorithm combined with the DSM strategies. A one-week load profile is compressed into a one-day average load profile in 1 hr interval time for simulation purposes for 24h's of load profile pattern. The analysis of case studies for both commercial and industrial tariff have been arranged as follows:

Case 1: Load profile of baseline of the flat tariff rate

Case 2: Load profile of E1/C1 with applied TOU- OPTR tariff rate without optimization

Case 3: Load profile of E1/C1 with TOU-OPTR tariff rate which applied 5% of the DSM strategies and PSO algorithm

Case 4: Load profile of E1/C1 with TOU-OPTR tariff rate which applied 10% of the DSM strategies and PSO algorithm

Case 5: Load profile of E1/C1 with TOU-OPTR tariff rate which applied 15% of the DSM strategies and PSO algorithm

Case 6: Load profile of E1/C1 with TOU-OPTR tariff rate which applied 20% of the DSM strategies and PSO algorithm

Case 7: Load profile of E1/C1 with TOU-OPTR tariff rate which applied 25% of the DSM strategies and PSO algorithm

Case 8: Load profile of E1/C1 with TOU-OPTR tariff rate which applied 30% of the DSM strategies and PSO algorithm

DSM strategies such as Peak Clipping, Valley Filling, and Load Shifting have been applied in each load profile where the maximum adjustment is set limited to 30% of the overall load. In the meantime, according to the formulation discussed in the previous section, the PSO algorithm was chosen as the main driver for those strategies to determine the optimal load profile for E1 and C1 consumers.

While searching the optimal load profile in simulation, the different total energy before and after the optimization must be below ±10% to reduce the difference in energy consumption from the regular operation. In addition, the value of the load factor improvement must also be greater than the load factor baseline to gain the reduction of the electricity cost.

A. Consumer tariff analysis: Industrial E1 type

Figure 1 illustrates the average baseline load profile for the industrial consumer under E1 tariff, which was poultry manufacturing. From the observation, the energy consumption of the manufacturer fluctuated from 8:00 AM until 12:00 PM and started to decrease until 4:00 PM before significantly rising until near midnight hour (12:00 AM). It was noticed that the energy consumption is highly consumed even at night to reduce the maximum demand during the day which will be charged a higher bill to the consumer. The minimum base load needed to support the daily operation of the factory is approximately 916kW.

Figure 2 depicts the obtained simulation load curve for cases E1 tariff, respectively, justifying the effectiveness of TOU-OPTR optimization versus existing E1 flat tariff and TOU-OPTR without optimization. The decrement of the loads during peak and mid-peak hours (about 99:00 AM-12:00 PM) before changing patterns vigorously (about 1:00 PM-9:00 PM) from the baseline in Case 1 shows the algorithm's performance to reach the minimum energy cost reflecting OPTR pricing.

Since the load clipping strategy is used in each load profile, the load consumption is reduced significantly below 50% for all optimal cases than the actual load profile during peak hour at about 11:00 AM. (Case 3: 26.84%; Case 4: 28.26%; Case 5: 47.31%; Case 6: 44.97%; Case 7: 19.83%; Case 8: 33.85%).

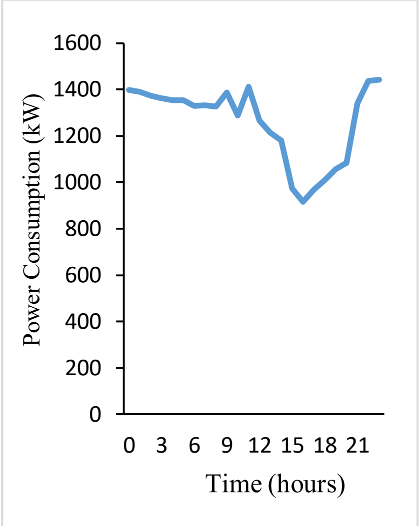

Figure 1: Average baseline load profile for E1 consumer in 24 hours

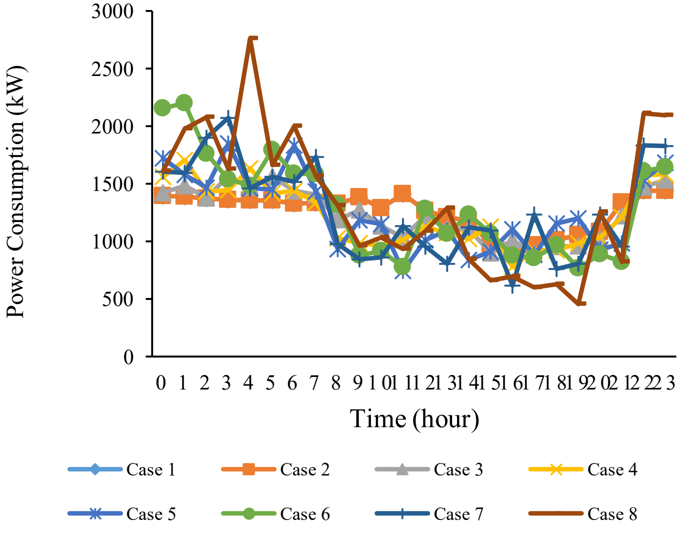

Figure 2: Simulation of optimal OPTR load profile E1

As a comparison during off-peak hour about 11:00 PM, the load consumption in optimization load profiles is increased steadily than the actual load profile up until 30% due to the impact of valley filling strategy in the proposed DSM strategies. (Case 3: 6.00%, Case 4: 8.85%, Case 5: 14.37%, Case

6: 12.34%, Case 7: 21.07%, Case 8: 31.24%).

Table 2 presents the best results obtained from the simulation which consist of the improvement of the load factor, the percentage of energy consumption different before and after optimization, MD value, the allocation of the MD in the load profile, and total electricity cost for daily operation accordingly. From the observation, Case 2 recorded the reduction of energy cost near to 7% even without optimization technique results from the discount during off-peak hour under the OPTR scheme.

However, the total electricity cost was only reduced to 1.28% due to the high cost of MD. Thus, with the application of optimization algorithm and DSM strategies such as peak clipping in each load profile were cut down the maximum demand cost in Case 3 (9.77%), Case 4 (14.09%), Case 5 (14.87%), Case 6 (6.73%), Case 7 (12.46%) and Case 8 (7.22%) which results in the reduction of total electricity cost simultaneously even with the peak location of MD value.

Case 5 gives the best optimal result with the highest reduction of total electricity cost up to 13% due to the lowest MD value and load factor improvement from the baseline in Case 1. Overall, the proposed formulation and optimization strategies reduce the MD and improve load factor with the least value of different energy consumption which is below 7% for all optimal cases.

Table 2: Comparison of all cases for E1-OPTR

Industrial E1 Tariff	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Energy Consumption (kWh)	30181.00	30181.00	29751.00	29307.00	30133.00	31089.00	30510.00	32074.00
Different (%)	-	-	-1.42	-2.90	-0.16	3.00	1.09	6.27
Maximum Demand (kW)	1412.00	1412.00	1274.00	1213.00	1202.00	1317.00	1236.00	1310.00
MD Location Zone	Peak	Peak	Peak	Peak	Peak	Off-Peak	Peak	Off-Peak
Load Factor	0.89	0.89	0.97	1.00	1.00	0.98	1.00	1.00
Energy Consumption (RM)	10170.10	9507.56	9362.88	9195.61	9434.28	9695.93	9511.79	9932.11
Maximum Demand (RM)	41795.20	41795.20	37710.40	35904.80	35579.20	38983.20	36585.60	38776.00
Total Cost (RM)	51966.20	51302.76	47073.28	45100.41	45013.48	48679.13	46097.39	48708.11

B. Consumer tariff analysis: Industrial E1 type

The average baseline load curve gained for the Total UTeM electricity consumption is shown in Figure 3. It can be noticed that the average energy consumption of the university gives a bell shape of load profile. Because the university serves as the main centre for academic purposes and other operations including administration, sports, and hostel accommodations for students leads to an increase in energy consumption during peak hours from 9:00 AM to 5:00 PM as shown in Figure 3. The baseload for the daily operation is observed to be approximately 500kW for 24 hours operation considering a large type of buildings which also covers for corridor lamp, streetlamp, and elevator for safety purposes at night.

Figure 4 illustrates the simulation load curves obtained for all cases in C1 tariff to evaluate the performance of optimization algorithm compared to other baselines flat tariff and TOU-OPTR tariff alone. The load shape of Case 8 for the total UTeM was observed to be much further from the baseline load since the highest percentage of DSM strategies is applied to the load profile.

It was noticed that the optimal load curve for Case 3 until Case 8 showed a fluctuating load curve during peak hours from 9:00 AM until 6:00 PM to meet the lower electricity cost as compared to the load curve for Case 1 and Case 2. Most of the optimal load profiles suggested starting the electricity operation early at 8:00 AM from the observation. The energy consumption curves started to rise rapidly since the energy charge is lower during off-peak hours than at peak hour (9:00 AM) in the baseline load profile.

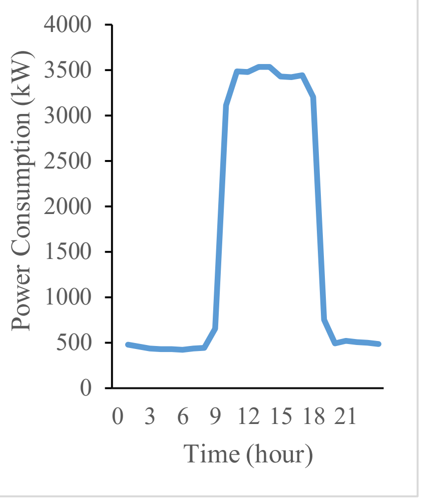

Figure 3: Average baseline for C1 consumer in 24 hours

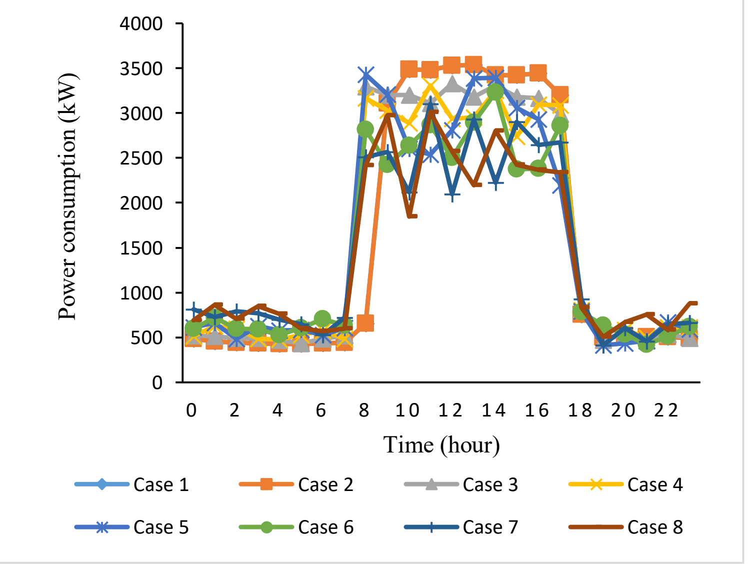

Figure 4: Simulation of optimal OPTR load profile C1

As can be seen, the energy consumptions are higher for all optimal cases compared to base Case 1 and 2 during off-peak hours from 10:00 PM until 8:00 AM to justify the impact of simultaneous DSM strategies used to manage energy consumption by reducing the demand in peak zone.

Table 3 presents tabulated data following the pricing results for the commercial tariff category. For tariff type C1, the cost saving is obtained in Case 2 instead of Case 1, where the university can gain 0.31% of total cost saving compared to baseline considering the discount offer in OPTR tariff rate for off-peak hours. Case 3 until Case 8 show significant reductions in total electricity costs indicating the promising results of DSM strategies and PSO algorithm in searching for the optimal load profile (respective saving Case 3: 5.08%; Case 4: 5.90%; Case 5: 3.04%; Case 6: 8.82%; Case 7: 12.12%; Case 8: 14.51%). The cost saving is steadily increased from Case 3 until Case 8, where the maximum of DSM strategies percentage is applied to the load profile. The load factor improvement from the baseline case has helped the university enjoy the OPTR tariff discount of up to 14%.

The proposed simultaneous strategies of DSM, such as Peak Clipping, Valley Filling, and Load Shifting were able to give positive results to the load profile of the university. For the optimal cases, the MD had been shifted to an off-peak hour in Case 5 only while the rest of the other issues were in peak hour. Nevertheless, the reduction of MD value is only around 2% from the base case and the least among the other cases, which results in the highest total electricity cost from the optimization cases. Hence, the value of MD is vital to obtain the reduction of the total bill since the MD charge is the same for each period in the TOU-OPTR tariff.

Table 3: Comparison of all cases for C1-OPTR

Commercial-C1(U) Tariff	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Energy Consumption (kWh)	38093.00	38093.00	39174.00	38407.00	37600.00	35475.00	35180.00	34811.00
Different (%)	-	-	2.84	0.82	-1.29	-6.87	-7.65	-8.62
Maximum Demand (MD) (kW)	3535.00	3535.00	3331.00	3309.00	3434.00	3229.00	3103.00	3012.00
MD Location Zone	Peak	Peak	Peak	Peak	Off-Peak	Peak	Peak	Peak
Load Factor	0.45	0.45	0.49	0.48	0.46	0.46	0.47	0.48
Energy Consumption Cost (RM)	13903.95	13525.62	13938.04	13617.35	13290.96	12502.56	12329.85	12188.37
Maximum Demand Cost (RM)	107110.50	107110.50	100929.30	100262.70	104050.20	97838.70	94020.90	91263.60
Total Cost (RM)	121014.45	120636.12	114867.34	113880.05	117341.16	110341.26	106350.75	103451.97

IV. Conclusion

From the discussion above, the PSO algorithm and formulation for OPTR tariff rate considering a simultaneous DSM strategy have been proposed and tested to the real industrial and commercial load profile. As a result, significant cost saving has been achieved, resulting from the reduction of maximum demand cost and load factor improvement under the OPTR pricing signal. The performance of the PSO algorithm is acceptable since it produces the optimal load profile and promising forecasting results for each case conducted under certain constraints. Thus, the given information can accelerate the application of AI for cost savings that can be expected. The notable findings concluded that the E1 and C1 consumers could enjoy more than 5% electricity cost reduction for most optimal cases when changing into OPTR tariff programs with the minimum percentage of DSM strategies.

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