

Effective Electricity Cost Management in a Manufacturing Operation by Using Optimal ETOU Tariff Formulation

M. F. Sulaima¹, N. Y. Dahlan², and Z. M. Yasin²

Abstract—In this study, simultaneous Demand Side Management (DSM) strategies are proposed for energy consumption cost reduction and peak load mitigation to industrial's consumers. By which, a real test case study of a manufacturing electricity load profile had been used to prove the concept. A superior bio-inspired algorithm, Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) had been implemented and compared in order to optimize the upright load profile of load management strategy. Subsequently, significant simulation results of operation profit gain through 24 hours power consumption had been analyzed properly. The proposed method had shown reduction of electricity energy consumption cost at all pricing zones; and Maximum Demand (MD) cost mitigation when load management weightages were applied to the identified 10% controlled loads consequently. The investigation has found that, the loads are manageable through the improvement of Load Factor Index (LFI) while Buildings' Electricity Economic Responsive Index (BEERI) has been the indicator to find the minimum requirement for the optimum load management weightages. Thus, it is hoped that the finding of this study can help to poise the industrial operation in terms of electricity cost effectiveness as well as support the national demand side management program.

Index Terms—Electricity Tariff, Time of Use, Maximum Demand, Load Factor Index, Demand Side Management

I. INTRODUCTION

Continuous energy generation from burning fossil fuel has led to the increasing of CO₂ emission. In the context of industrial building's electricity demand, it is reported that 50% of the global energy consumption is required by the buildings for operation, which also contributes to approximately 80% of global warming [1]. The electricity consumption by industrial consumers is indeed for a major concern in many countries including Malaysia. Since new electricity tariff structure was implemented in 2014, there has been a slight increase in

electricity price, up to 20% compared to the baseline price of 2013. Currently in Regulatory Period Two (RP2), the base rate

that has been announced by the government in December 2017 has moved up to 39.45sen/kWh starting from January 2018; compared to previous Regulatory Period One (RP1) (2015-2017) which was 38.53sen/kWh [2]. In reflecting to the price upsurge, there is demand pricing signal program through new tariff modality introduced in 2016, which is called Enhance Time of Use (ETOU) tariff. The ETOU tariff program consists of three time zones which are Peak, Mid Peak and Off Peak, with different rate for each zone. Instead of conventional flat tariff for C1-commercial & E1-industry, and time of use with two zones of peak & off peak for C2-commercial & E2-industry; to promote demand side management through peak load reduction is the main objective of the ETOU tariff. In the meantime, the general benefit of the ETOU will go to consumers through billing reduction, and the providers' generation critical peak demand will be able to mitigate respectively. Details of specific time zones of ETOU tariff in Peninsular Malaysia is presented in [3], [4] while the examples of tariff time zones in other countries are presented by India in [5], China in [6], and Brazil in [7] respectively.

In the other hand, during the introduction of new tariff structure, the tariff pricing has been increased concurrently. The increase of electricity price has a direct impact on the industries' consumer especially production type of manufacturing, such as increasing the cost of operation and reducing the effectiveness of the budget operational account [8], [9]. With regards to this problem, ETOU tariff has indeed come at the right time, but until today there is no concrete formulation that proves the concept on how industrial consumers are able to reduce the electricity cost smartly. Even though the ETOU has been in market for quite a while, it was reported that less than 1% of commercial and industrial consumers join the program [10]. It

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is due to several factors has contribute to that, such as less communication between electricity provider and consumers for the load management awareness while consumers' side do not have proper strategy in order to deal with ETOU as to as enhance their knowledge to manage electricity load profile. Due to that reason, in this study, we provide knowledge sharing in order to help demand side consumer in dealing to ETOU program such below:

- (a) Introduce a novel of simultaneous formulation for six-time segmentation of Peninsular Malaysia ETOU tariff by considering optimal electricity consumption cost reduction and peak demand charge mitigation as well as produce better reference load curve in regards to specific industrial consumer.
- (b) Provide a better technique of load management by combining several DSM's strategies such as valley filling, load clipping and load shifting and engage them to bio-inspired algorithms, which are Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO).
- (c) Introduce consideration of fundamental concept of effective load management indicator by measuring the performance of Load Factor Index (LFI) and Buildings' Electricity Economic Responsive Index (BEERI). Both improvements are important in order to show that the Maximum Demand (MD) cost and electricity cost consumption (kWh) has been reduced while optimum weightage of controlled load would be defined accurately

This study has investigated and compared the test results of industrial flat tariff E1, TOU tariff E2 and conventional ETOU tariff E1 respectively. The real test baseline load profile was taken from an electronic based production manufacturing in southern Peninsular Malaysia. By this way, the modality ETOU tariff program can be promoted; as the same time reducing the manufacturer's electricity cost burden simultaneously. The rest of this paper is structured as follows. Section II briefly reviews some of related work to the proposed studies. Section III presents the optimal ETOU formulation for consumers while Section IV explain the implemented optimization algorithm accordingly. Meanwhile Section V discusses the analyses on the data results, and Section VI presents the conclusion for the study.

II. LITERATURE REVIEW

A. Demand Side Management Strategies in regards to Industrial TOU Tariff

The early stage of the literature review only discusses on the general commercial and industrial's consumers to reflect to the variety of electricity tariff, but the scope of works on specific related studies to Time of Use tariff (TOU) under simultaneous demand side management (DSM) strategies "optimization" has not yet been discussed. Thus, as best of our knowledge, the TOU study in regards to the implementation of optimization algorithm has been divided into three categories which are; TOU load management that apply DSM strategies, TOU tariff design, and TOU with load scheduling (machine or operation system scheduling).

Since there are less studies for manufacturing's consumer regarding the implementation of DSM strategies and application of bio-inspired algorithm under scope of TOU tariff, we decide to perform the critical investigation about it. The state of art of those related works found are on the context of load scheduling but little on load profile optimization strategy. As in previous section, optimization of load scheduling in industrial type TOU environment has been highlighted in few others references such as in [11] and [12]. PSO based algorithm has been applied while the objective of the operation cost optimization in line with load scheduling as well as concern about the manufacturer revenue. In conjunction to swarm base algorithm performance and load scheduling technique, the Evolutionary Algorithm (EA) optimization technique was introduced to deal with load shifting, specifically for standard machineries in residential, commercial and industrial consumers in reflect to promote cost saving under new tariff initiative such as Time of Day (TOD) , as reported in [13] and [14]. Meanwhile, optimization on specific system such as water heater and heat pump relative to TOU pricing has been reviewed in [15] and [16], respectively. In the studies, GA and PSO was applied in a controller to shift the schedule of water heater in order to find the optimal cost for heat pump and thermal storage scheduling.

In the other hand, DSM strategies that consist of Peak Clipping, Conservation, Load Building, Valley Filling, Flexible Load Shape and Load Shifting are the examples of possibility strategies to be used for load profile management. Most researchers who implement the strategies for load profile management such as Peak Clipping in [17], [18], Conservation in [17], Load Building, Valley Filling in [6], and Flexible Load Shape and Load Shifting in [19], [20], [21], [22], [23] have applied the strategies in single application for different load profile. Nevertheless, most of them had not been applied as concurrent strategies while the application limit commercial and residential load profile electricity consumers only.

With regards to the Malaysia ETOU tariff, several studies have been given priority to date. Conventional load shifting to industrial and commercial type of consumers in order to mitigate the electricity cost has been proposed in [24] and [25]. However, the studies did not propose any related solution toward implementation of others DSM strategies as well as apply the optimization algorithm. Meanwhile the formulation of the optimal ETOU cost is only based on three related zones not in related six time segmentation as proposed by us. Therefore, in this study, ACO and PSO algorithms has been applied in order to achieve optimal solution in the environment of simultaneous Peak Clipping (PC), Valley Filling (VF) and Load Shifting (LS) implementation strategy. The desired formulation reflects the Malaysia ETOU tariff structure, as to as optimize the cost of MD and electricity consumption accordingly. To understand the industrial tariff as well as industrial's electricity pricing in Peninsular Malaysia, we present the overview of it in the next section. Meanwhile details explain of propose formulation of optimal industrial ETOU tariff to optimization algorithms with certain constraints will be explained in section III.

B. Industrial Consumer Electricity Tariff in Peninsular Malaysia

The difference between ETOU and conventional tariff is that, ETOU has an additional zone of time which is mid-peak. The peak period has been reduced from 12 hours to 4 hours only and off-peak maintains the same period of time zone as conventional TOU tariff. The consumers receiving the flat tariff in conventional industry medium voltage D & E1 will be able to enjoy time of use tariff program, as well as open opportunity to get cost reduction. Table I and Table II present the TOU and ETOU tariff rates for industrial tariffs by provider.

TABLE I
FLAT & TOU TARIFF RATE (2014-PRESENT)

Tariff Category	MD: RM/kW	Peak: sen/kWh	Off Peak: sen/kWh
Industrial D (LV)	NA	38.00<(200kWh)<44.10	NA
Industrial E1 (MV)	29.6	33.7	NA
Industrial E2 (MV)	37	35.5	21.9
Industrial E3 (HV)	35.5	33.7	20.2

TABLE II
ETOU TARIFF RATE (2016-PRESENT)

Tariff Category	Demand Charge (RM/kW/Month)		Energy Charge (sen/kWh)		
	Peak	Mid-Peak	Peak	Mid-Peak	Off Peak
Industrial D (LV)	42.1	37.2	48.4	32.7	24.9
Industrial E1 (MV)	35.5	29.6	56.6	33.3	22.5
Industrial E2 (MV)	40	36	59.2	33.2	21.9
Industrial E3 (HV)	38.3	35	57.6	32.7	20.2

III. ETOU FORMULATION FOR CONSUMERS

Since the ETOU formulation is expressed in pricing unit where the objective function of the simulation is to optimize manufacturing's buildings that registered under ETOU program as well as ETOU load curve rearrangement should be done. Hence, the general of optimum ETOU electricity energy (RM/kWh) has been written in (1):

$$\Delta ETOU_{eCost} + MD_{Optimum}^{Cost} \quad (1)$$

$\Delta ETOU_{eCost}$, is the electricity cost of desired load curve after DSM strategies are applied, which reflects six-time segmentation price base, as presented in (2) accordingly.

Meanwhile the optimum Maximum Demand MD_{MP}^{Cost} allocation and mitigation will be discussed in the constraints part.

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

Where,

ΔP_{op} = changing of off peak desired load curve with changing of time, $N=10$;

ΔP_{mp1} , ΔP_{mp2} , ΔP_{mp3} = changing of mid peak desired load curve with different time change, $N=3$, $N=2$ and $N=5$, respectively;

ΔP_{p1} , ΔP_{p2} = changing of peak desired load curve at time changing $N=1$ and $N=3$ separately;

TP_{op} = utility ETOU tariff price for off peak time zone;

TP_{mp} = utility ETOU tariff price for mid peak time zone;

TP_p = utility ETOU tariff price for peak time zone;

The general total solution of DSM strategies selection for six-time segmentation profile can be written as in (3). Demand side strategies which had been proposed to be included were Valley Filling (VF), Peak Clipping (PC) and Load Shifting (LS).

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

where $\Delta P_{ts,i}^{VF}$, is the changing amount of desired load based on VF strategy by DSM at random load (i) in time segmentation (ts). $\Delta P_{ts,i}^{PC}$ and $\Delta P_{ts,i}^{LS}$ are the changing amount of desired load based on PC and LS strategies by DSM at random load (i) in time segmentation (ts) respectively. Meanwhile, the lower bound and upper bound of random load setting selection (i) had been set as in (4) in order to reflect controlled apportionment accordingly.

$$0.005 \leq i \leq 0.10 \quad (4)$$

Temporarily, W_{VF} , W_{PC} , and W_{LS} are the weightage of DSM strategies to be implemented in every single load profile concurrently; which is set by consumers depending on the percentage of load management ability setting at particular time segmentation that commonly set 0% to 100%. This weightage will be classify to the several cases due to the changing of it will affect the aptitude of the DSM strategies and performance of optimization algorithm.

Apart from that, the constraints of the demand side strategies to achieve satisfying performance had been decided as follows:

a. Constraints for VF

$\Delta P_{ts,i}^{VF}$, will be selected during time segmentation with minimum value of base load price. The (ts) adjustment of VF selection must be as

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

b. Constraints for PC

$\Delta P_{ts,i}^{PC}$, will be selected during two highest price of time segmentation loads as well as where the maximum demand is located, where (ts) adjustment of PC selection must be as

$$\text{Average load price} < \Delta P_{ts,i}^{PC} \leq \text{Max base load price} \quad (6)$$

c. Constraints for LS

LS in the ETOU program shall lead to perform at randomly selected three time segmentations, different from the previous formulation by [24] who proposed ETOU load shifting to be best from peak to mid-peak time zone. However, in this investigation, especially for the simultaneous DSM strategies application, the best way to put LS is after VF and PC selection, while the rest of time segmentations will be the location for LS to perform randomly. The process of the proposed LS procedure in ETOU load profile is written as in (7), (8) and (9) accordingly.

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

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

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

Where,

$\Delta Z_{\text{down}}^{\text{shift}}$ = changing of load decrease at certain time segmentation (ts) for the load, i ;

$\Delta Z_{\text{up}}^{\text{shift}}$ = changing of load increase at certain time segmentation (ts) for the load, i ;

ω = the random weightage of load decrease and increase at lower bound and upper bound load setting as in (4).

d. Constraints for optimal Maximum Demand (MD) selection

An important element of the ETOU tariff cost reduction on the demand side is Maximum Demand. In Equation (1), $MD_{\text{optimum}}^{\text{cost}}$, is the variable to $ETOU_{\text{min}}^{\text{cost saving}}$. Due to that reason, optimal selection and arrangement of MD at particular time segmentation are crucially needed. First, the arrangement of the Maximum Load for each time segmentation must be identified, where the segregation of MD at mid-peak load and peak load are determined, respectively. The selection of MD at a daily power (kW) capture is by mapping to both MD costs, either mid-peak charge or peak charge but the optimum of the will be the lowest cost at all. Equation (10) and (11) summarize the selection of MD power load to respective MD charge congruently. Meanwhile (12) shows the optimum MD charge obtained through selection of the combination from both peak and mid-peak selection accordingly.

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

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

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

Where,

$MD_{\text{MP}}^{\text{cost}}$ = Optimum power load selection at Mid-Peak area;

$MD_{\text{P}}^{\text{cost}}$ = Optimum power load selection at Peak area;

L_{Tn} = Selected power load for n number at particular time segmentation (ts);

$MD_{\text{MP}}^{\text{TP}}$, and $MD_{\text{P}}^{\text{TP}}$ = the MD charge for different mid-peak and peak

e. Constraints for total energy

Total energy before and after of the optimization throughout the process of demand side strategies should not be more than $\pm 5\%$ [26]. Equation (13) describes the constraints of six segmentation for total energy consumption (kWh) before and after optimization consequently.

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

Based on all the optimum formulation and effectiveness of the constraints setup for two variables in load profile adjustment, which are energy and power demand, the verification of the load profile improvement would be referred to Load Factor Index (LFI) as shown in (14).

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

Where $MD_{\text{Optimum}}^{\text{kW}}$ is optimum selection of MD (kW) at peak or mid peak zones, $\sum E_{TSn}$ is total electricity consumption for total n time segmentations, and t is time of electricity usage. According to the command procedure, lower MD arrangement in load profile leads to more improvement of LFI. In the other hand, LFI also refer to the load response indicator which is measured form 0 until 1 with can be converted to percentage of hundred as maximum value. The ability of demand response is depending on the initial index; while the mitigation peak demand program able to improvement LFI expressively.

Equation (15) represents the most correlated measurement performance of load management indicator which is Buildings' Electricity Economic Responsive Index (BEERI). Different to Energy Efficiency Index (EEI) [27], or most command also called as Building Energy Index (BEI) has consisted of specific energy related consumption not limited to electricity only; where BEERI focus on electricity economic based on load management with "optimal percentage" response to the multiple zones of utility tariff only. In propose of BEERI, our priority concern is to overlook and standardize the correlation of MD cost optimization (as in (12)) & Energy Cost optimization (as in (2)) to the impact of total electricity cost (as in (1)) respectively. Without considering any uncertainty to the measurement such in [28], the range setting of BEERI is from 0 to 1 while the improvement of it must be less than baseline value. Noted that, not all energy cost saving will produce good results of BEERI, because of this index consider both demand cost and total energy cost for the sustainable economic load management balancing as well as most optimal weightage of load management to be initially applied by consumers.

$$BEERI = \frac{MD_{Optimum}^{Cost}}{ETOU_{cost}^{optimal}} \quad (15)$$

IV. OPTIMIZATION ALGORITHM

To examine the effects of conventional tariff and ETOU tariffs on LFI and BEERI; as shown in Fig. 1, the optimization of MD and electricity consumption to the respective DSM strategies is accomplished based on ACO and PSO algorithms for the purpose of comparison and validation.

A. Ant Colony Optimization (ACO)

ACO Inspired by an ant colony foraging behavior, ACO uses the element of ant attribute to find the optimal path to the food source. In natural environment, pheromone is the communication channel for the ants to move around in finding possible food source through signal paths [29]. Depositing pheromone establishes the communication between ants, where the stronger the pheromone, the longer the path. By the process of mimicking, the ant in ACO represents possible solution that consists of a set of nodes that have been visited by the ant in the line so far. Hence, when the next ants want to choose the nodes, these ants will possibly select the ones with highest level of pheromone. This situation contributes to the convergence of the optimal solution. Normally, ACO algorithm is developed in two importance parts, which are the processes of generating the ants, and updating pheromone [30]. In part 1, the ACO process consists of generating a new set of ants in each iteration according to the desired nodes. The probability of an ant to select a certain node can be expressed using (16) accordingly.

$$p(a_{ij}|S_p) = \frac{r_{ij}^\alpha * \eta_{ij}^\beta}{\sum r_{ij}^\alpha * \eta_{ij}^\beta} \quad (16)$$

where:

$p(a_{ij}|S_p)$ = the probability of limit a_{ij} will be chosen in line to the partial solution S_p

a_{ij} = the limit from node i to node j

r_{ij} = the pheromone values at a_{ij}

η_{ij} = an heuristic value, typically the inverse of the cost of going through a_{ij}

α = the pheromone importance factor

β = the heuristic importance factor

Now, once the ant has evaluated its solution and calculating its fitness value, the value will be used in the following part 2, which is updating the pheromone process. This is where the level of deposited pheromone is identified. The increase of the pheromone value in trail as the ant deposits will strongly limit the connecting nodes it has used. In conjunction to that, there is possibility of decreasing of the

pheromone level as well; the process is called evaporation. Equation (17) and (18) illustrate the updating process of pheromone evaporation and reinforcement, respectively.

$$r_{ij} = (1-\rho) * r_{ij} \quad (17)$$

where:

r_{ij} = pheromone value at the limit from i to j

ρ = pheromone evaporation factor

$$r_{ij} = r_{ij} + \sum \Delta r_{ij} \quad (18)$$

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 depends on the length/cost of the path taken by the ants. Various attempts have been made by researchers to find the best solution, especially in engineering work. The steps for the ACO algorithm that has been applied in this study are as follows:

Step-1: Initialization of ants by setting $\alpha=1$, $\beta=0$ for (16) and $\rho=0.3$ for (17), as referred from [31]–[33]. The ants represent a set of possible initial load profile to determine single 24-hour of change in each electricity energy cost of electricity, called as nodes. The fitness values will be used for update of gathering more ants to proceed to the next step.

Step-2: Formulating the constraints and determining the Cost. The updated pheromone values will be used to engage in the formulation of optimal ETOU electricity energy cost as to as MD cost and the DSM strategy as in (2) until (12) respectively. The update of total electricity energy cost in six-time segmentation will be used as the best Cost value in ACO process part 1, then to proceed to find the updated ants pheromone in part 2.

Step-3: The best total energy cost for all segmentations is determined by best Cost value during pheromone update, while the best ants to symbolize optimal load profile is created concurrently. Again, (17) and (18) are applied in this step.

Step-4: When the criterion for the best Cost has been fulfilled, the significant value of Cost is decided to be the convergence value to fulfill the set of constraints as well. If not, the list of new possible optimum setting of ants will take part, which means going through the process all over again. At this stage, the contribution of electricity energy cost and MD cost to the contribution of LFI and BEERI is generated.

B. Particle Swarm Optimization (PSO)

Authors in [34] has introduced PSO algorithm for the first stage and has been updated by [35] to add the weightage factor in the equation to find the best solution. The concept of PSO was inspired by birds and fish schooling, while PSO has been basis of comprising between new algorithms to test their

superiors. The stage of implementation of PSO algorithm in determining optimal electricity energy cost as follows:

Step 1: Initialization. The process starts with the initialization of population, which is determined by calling dailyload profile in 24-hours, as to as present consumers' energy consumption pattern. Those variables are generated by the system via a random generator available in the program to compute the electricity cost for the profile in the next step. PSO parameters are then initialized, such as number of particles N , weighting factors, $C1$ and $C2$ and maximum number of iterations. In order to ensure the effectiveness of energy cost, optimization is maintained, and all the constraints as in (5) until (13) are applied strategically.

Step 2: Fitness Calculation. An initial population of particles with random position, and velocities, in dimension in the solution space is randomly generated. For each particle that fulfills the constraints as in initialization stage, the load profile will be analyzed and the total ETOU electricity energy cost and MD cost is calculated by using (2), by adopting the correlation from (3), (4) and (12) simultaneously. Meanwhile, the input of the calculation and constraints is used to calculate LFI & BEERI as well (refer (15) and (16)).

Step 3: Determine P_{best} and G_{best} . During the searching process, the two best values are updated and recorded. These values are related with the best solution that has been extended so far by each particle which retains path of its coordinate in the solution space. This value is noted as P_{best} and another best value is G_{best} , which is the whole best value so far by any particle. The P_{best} and G_{best} represent the generation of best ETOU energy consumption cost which also has contributed to generate optimum MD cost concurrently.

Step 4: New Velocity and Position. In this process, the particles' velocity and position is updated by applying (19) and (20), respectively. The particle's velocity signifies a load profile curve changing. Meanwhile, the total load profile in all segments is evaluated by using the new position. The new position set will be tested for convergence. If convergence is not achieved, the process will be repeated.

$$V_j^{k+1} = (\omega \times V_j^k) + (C_1 r_1 (P_{bestj}^k - X_j^k)) + (C_2 r_2 (G_{bestj}^k - X_j^k)) \quad (19)$$

$$X_j^{k+1} = X_j^k + V_j^{k+1} \quad (20)$$

Where,

V_j^k = velocity of particle j in iteration k

X_j^k = position of particle j in iteration k

ω = inertia weightage

P_{bestj}^k = the best value of fitness function that has been achieved so far by particle j in iteration k

G_{bestj}^k = the best value among the fitness values

C_1 & C_2 = constants that represent weightage factor of random acceleration terms

V_j^{k+1} = new velocity

X_j^{k+1} = new position

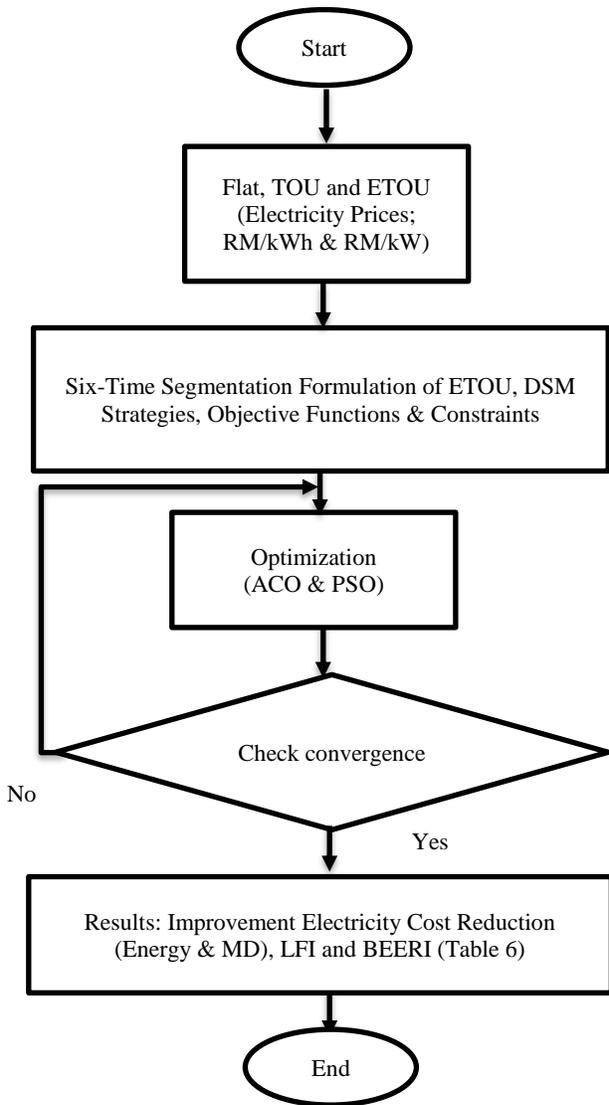


Fig. 1. Study flowchart and simulation.

V. RESULTS & ANALYSIS

In order to understand the output of this study, this section will details out the case study information. Meanwhile, investigation analysis are discussed in other next subsection with consist of total comparison of two different applied algorithms in validating the optimal formulation for the Malaysia E1 (MV) ETOU industrial tariff (as targeted tariff to be switched).

A. Case Study

To prove the effectiveness of the formulation and efficiency of the proposed algorithm, tests had been conducted by using load profile of an electronic manufacturing. A one-year profile had been collected, which was then compressed into 2 weeks profile while was averaged into 1-day load profile which is within 24 hours' time. Fig. 2 shows a part of the weekly profile as the reference for the readers. Data of electricity energy profile had been measured through energy meter at 11kV substation's busbar. For the analysis of the results in line to DSM strategies, the arrangement of the cases study by weighthage had been set as follows:

Case 1: baseline of the existing flat and TOU tariff rate

Case 2: E1 ETOU tariff rate without DSM strategies and optimization

Case 3: E1 ETOU tariff rate by using 20% of the DSM strategies and ACO/PSO algorithms

Case 4: E1 ETOU tariff rate by using 50% of the DSM strategies and ACO/PSO algorithms

Case 5: E1 ETOU tariff rate by using 80% of the DSM strategies and ACO/PSO algorithms

Case 6: E1 ETOU tariff rate by using 100% of the DSM strategies and ACO/PSO algorithms

Note that the controlled load to be adjusted was only available at 10%, which had been identified during the detailed load apportioning assessment at site. Hence, adjustment of the load management weightage had been set from 20% to 100% within the limitation of 10% controlled load only. In Fig. 3, the load apportioning for the most electricity consumption per system by end user is presented accordingly. The identified adjusted controlled load of 10% to be proposed was the 150HP compressor system. The rearrangement of the workers schedule was significant to the machine operational time that required compress air system to be ran was identified but will not be considered in this study. Analysis on the issue of the tariff transform into ETOU E1 type based on the 6 Cases will be explained in the next sub section accordingly.

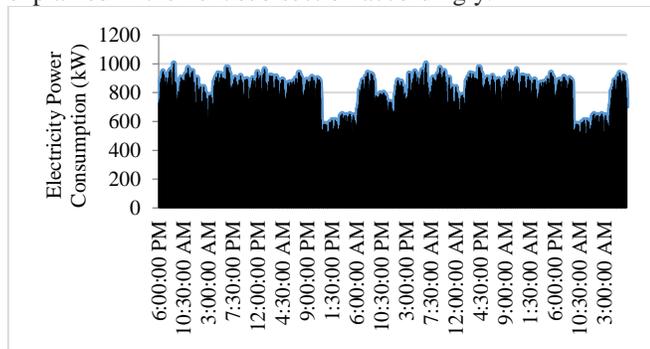


Fig. 2. Two-week electricity power consumption profile.

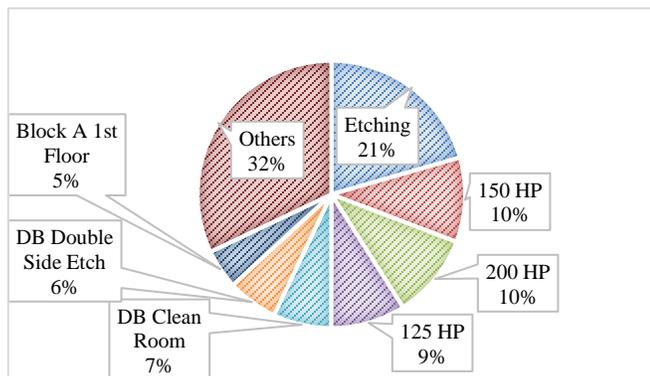


Fig. 3. Load apportioning.

B. Analysis of Load Profile

The obtained energy consumption profiles after simulation were divided in two parts which were ACO and PSO algorithms application as presented in Fig. 4 and Fig. 5 respectively. There was observed that, the implementation of optimal simultaneous DSM strategies had given significant impact to the movement of the load value during 24 hours operation of manufacturing.

It was highest demand at off peak zone which was on 22:00pm to 4:00am while demand was started to drop during rest hour on 17:00pm to 9:00pm. The energy profiles were produced by ACO’s cases had been remarked to be more stable and consistence compared to energy profiles that has been produced by PSO’s cases. However, both algorithms shape the same load curve when they were compared to baseline Case 1 and Case 2 on 9:00pm to 10:00pm where load was arranged to be increased. This situation of load increased in off peak zone was analyzed due to impact of valley filling and load shifting strategies congruently. Meanwhile the rest of load arrangement was noticed to slightly decrease during mid-peak and peak zones on 8:00am to 16:00pm due to peak clipping and load shifting strategies employment without changing the general load patent of initial baseline manufacturing operation. Instead of huge changing of the load curve when it was compared to the real operation, the significant DSM strategies come with proper determination of load management weightage has benefited building’s owner in order to manage appropriate loads in economic efficiency way.

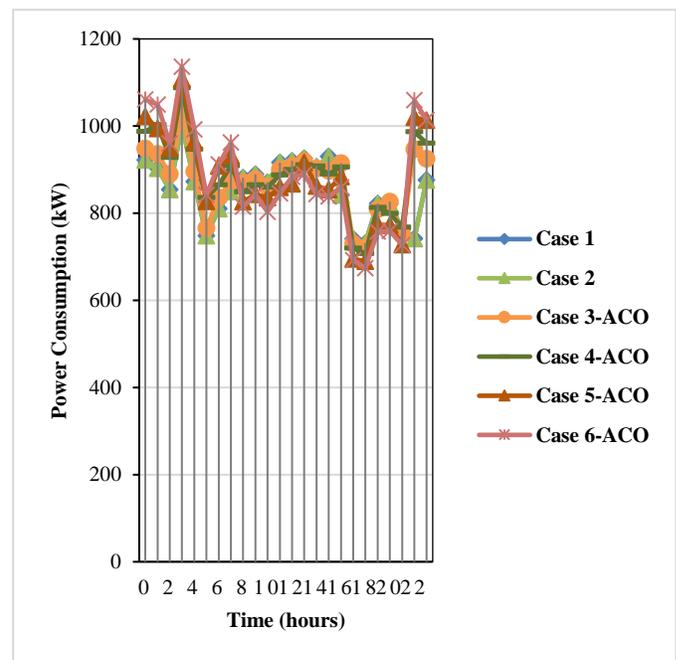


Fig. 4. Load profiles of ACO to baseline.

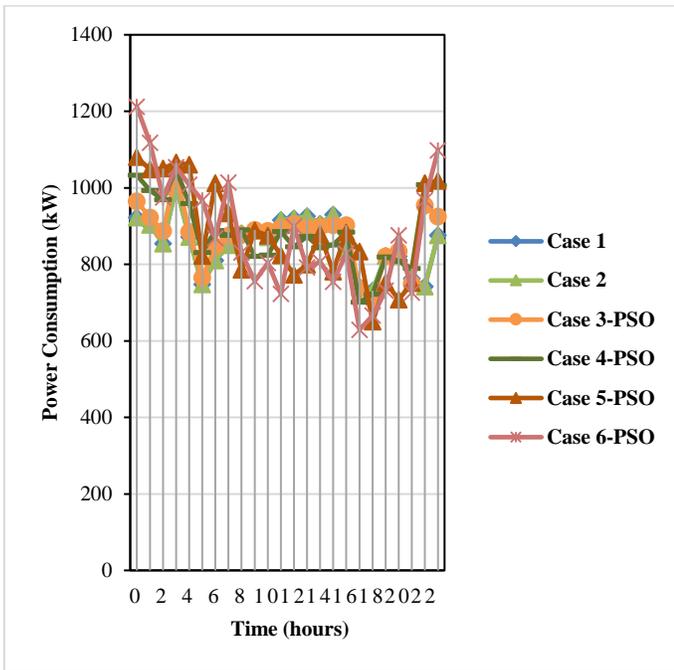


Fig. 5. Load profiles of PSO to baseline.

C. Analysis of Cost Effectiveness

As presented in formulation strategies that ETOU tariff has been segregated into six segmentations which were represent the adopted of time zones arrangement accordingly. Consequently, in this assessment of the cases were tested, we present the overall observation per segments optimization process by both algorithms. As determine in Table III, the energy consumption cost for the three baseline cases which were using flat and TOU tariff rate (Case 1 and conventional ETOU E1's rate (Case 2) had shown the different prices where the minimum of it was recorded by Case 1 TOU. In regards to the adjustment of the simultaneous DSM strategies and algorithm implementation, there was obtained that the energy consumption cost for Cases 6 of both ACO and PSO were minimized accordingly. Since ETOU has offered different pricing for different time zones compared to TOU and flat tariff, the overall optimization results of the energy consumption cost were reduced started since Case 3 (ACO & PSO) when it was compared to Case 1 and Case 2. It was noticed that, without any strategy apply to the current load profile, the energy consumption cost was reduced approximately 2.48% compared to flat tariff as presented by Case 2 accordingly. Since the MD allocation of Case 2 was in peak zone, there was noted that the cost of MD was slightly higher compared to Case 1. Nonetheless, through the effectiveness of the proposed DSM strategies come with implementation of bio-inspired algorithm (ACO and PSO); the impact of load management for the overall ACO and PSO cases in using ETOU rate has proven to be able to reduce the cost for energy consumption and maximum demand simultaneously. As in Fig. 6, the tabulated data of energy consumption pricing in six segmentation derivation has been properly accessible while the supporting Fig. 7 and Fig. 8 elucidates the performance of the algorithm iteration and optimum load profiles patents for the best obtained results so far. The energy cost for the Segment 1 (S1 off peak) had been increased dramatically in line to the increase of load

management weightage as Case 6-ACO and Case 6-PSO contributed for about 12.80% and 16.78% one-to-one. Meanwhile, the energy cost for peak zones (Segments S3 & S5) and mid peak zones (Segments S2, S4 and S6) had been maximized reduced approximately 3.5% to 8.4% at peak zones; and 9.3% to 10.3% for both Case 6's ACO and PSO respectively. The overall performance of the propose formulation of the ETOU optimization has contributed to save the energy cost up to 5.2% (Case 6-ACO) and 6.6% (Case 6-PSO). Different to the method that was proposed by [24], the proposed formulation only help to find percentage of the load to be transferred but not cover holistic and balancing cost for all the segments (time zones) that should be focused on the realistic condition for instance mapping them to the appropriate controlled load at site assessment. Simultaneous optimum DSM's strategies of load management formulation and constraints were able to maximize billing profit as the same time increase the economic efficiency through better tariff selection. The constraints proposed in [18] has been referred for this study where our proposed technique through combination of the concurrent peak clipping, valley filling and load shifting strategies in the single load profile has been better advantaged. This was proven by producing better results such to reduce the energy cost and optimum coordinate optimum MD cost for the multiple zones of electricity time base tariff. Hence in this study, better MD results was generated and observed in order to enhance the impact of total electricity cost reduction as to as improve the Load Factor Index (LFI) significantly. As illustrated in Table III, there were proportional reduction of the MD cost to the total electricity cost for both cases of ACO and PSO. It was leant that in order to sustain MD cost reduction, the location of the MD should be moved to mid peak areas while maintain the load curve in line to baseline of manufacturing operation needs. In this results performance, through multiple consideration to produce better results, it was declared that the contribution in this study was different to others such in [36] (had considered load shifting only limit to reduce energy cost but not considered maximum demand); [14] (had proposed consideration of peak demand mitigation and load shifting technique only but not deliberate the demand side strategies properly); [13] (had presented the load shifting method in real time pricing where the forecast and real simulation results were observed to much different compared to baseline consideration). In this study, the Case 6-ACO and Case 5-PSO had contributed to minimum the cost for the total electricity bill (energy (kWh) cost and MD cost) accordingly. It was noticed that the value of the MD and location in mid peak zone has brought those Cases to be better although not in maximum weightage of load management adjustment. The reduction of the MD cost for about 7.8% and 8% has contributed to the improvement of LFI. Better LFI value indicates the effectiveness of the demand response program as well as DSM strategies has been successful adopted congruently. Still, good value of LFI not presents the economic responsive towards minimum weightage of the controlled load to be applied. Meanwhile the actual condition of the decision making to be made in controlling the operation should be accurate and secured so that the efficiency of the tariff selection would be valuable in supporting cost saving program in industry. Due to that reasons, next section of the analysis and discussion will be

elaborated more on why simple ration of the MD and total cost as well as BEERI is proposed and how it works in order to help consumers to make decision in setting up the optimum percentage of load management to be implemented.

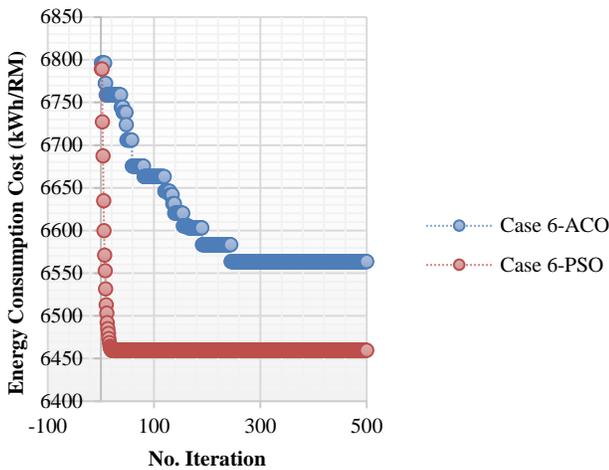


Fig. 7. Optimum pricing convergence value for ACO and PSO.

strategies that has been applied to the manufacturing operation system. Since BEERI as the ratio of the tariff modality which was MD cost to total electricity cost; the indicator performance of BEERI would be referenced for the truthful decision of the manufacturing operation to select the percentage of the controlled load to be involved. Meanwhile, in the phase of the load management strategy, BEERI will be one of the important information before the real execution demand response program would be entered. Such as in this case, the best performance of BEERI was recorded at Case 6 for ACO algorithm (improvising about 0.53%) and Case 4 for PSO algorithm (improvising about 0.60%) accordingly. It was analyzed that there were only 6% and 5% of load management in respect to Case of ACO and Case of PSO shall be involved in order to gain virtuous total of electricity cost saving. In the other hand, it was agreed that during the MD was located at Peak zone area, the performance of BEERI was not drop while the value of total electricity cost increase tremendously. Meanwhile, the overall performance of ACO algorithm in sustaining the improvement of BEERI was consistent but PSO algorithm consist Case 6 did not improve well. As mentioned early, it was proven that PSO algorithm was not consistent in determining the optimal results but able to find better result in enhancing the performance of BEERI.

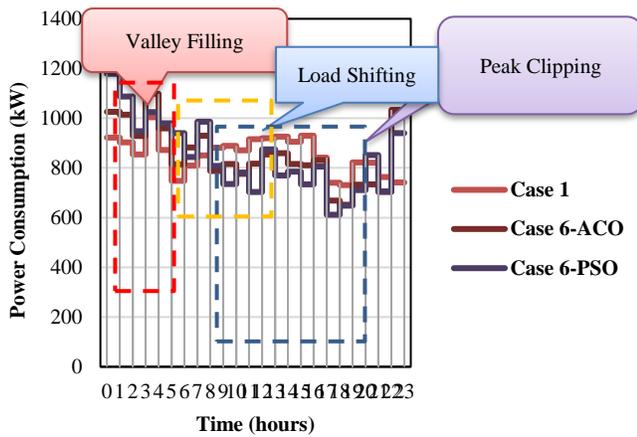


Fig. 8. Case 6 (ACO) and Case 6 PSO load profiles against baseline load profile.

D. Analysis of Economic Efficiency Responsive

As presented in Fig. 9 and Fig. 10, it was observed that the value of the LFI did not correlate to BEERI where several cases had revealed that; although LFI was improved but BEERI not. The regression analysis has been made to show the difference of that. The value of R^2 was 0.552 specifies that the correlation of them were under statistical standard. Due to that reason we could clarify that, LFI was the indicator to show the performance of the MD arrangement in demand response program while the improvement of that will improve efficiency of the DSM's

TABLE III
TOTAL OUTPUT OF THE SIMULATION RESULTS

Cases	Energy Consumption (kWh)	Diff (%)	MD (kW)	MD Location	Energy Consumption Cost (RM)	MD Cost (RM)	Total Electricity Cost/day (RM)	LFI	BEERI
Case 1 Flat	20,540	NA	930	Peak	6,921.98	27,528.00	34,449.98	0.9203	0.7991
Case 1TOU	20,540	NA	930	Peak	6,124.68	34,410.00	40,534.68	0.9203	0.8489
Case 2	20,540	NA	930	Peak	6,750.47	33,015.00	39,765.47	0.9203	0.8302
Case 3-ACO	20,543	0.01	901	Mid Peak	6,707.21	26,669.60	33,376.81	0.9500	0.7990
Case 4-ACO	20,540	0.00	878	Mid Peak	6,654.28	25,988.80	32,643.08	0.9747	0.7962
Case 5-ACO	20,540	0.00	889	Mid Peak	6,599.47	26,314.40	32,913.87	0.9627	0.7995
Case 6-ACO	20,538	-0.01	860	Mid Peak	6,556.86	25,456.00	32,012.86	0.9951	0.7952
Case 3-PSO	20,540	0.00	883	Mid Peak	6,697.93	26,136.80	32,834.73	0.9692	0.7960
Case 4-PSO	20,540	0.00	863	Mid Peak	6,613.94	25,544.80	32,158.74	0.9917	0.7943
Case 5-PSO	20,541	0.00	856	Mid Peak	6,541.45	25,337.60	31,879.05	0.9998	0.7948
Case 6-PSO	20,544	0.02	874	Mid Peak	6,464.23	25,870.40	32,334.63	0.9794	0.8001

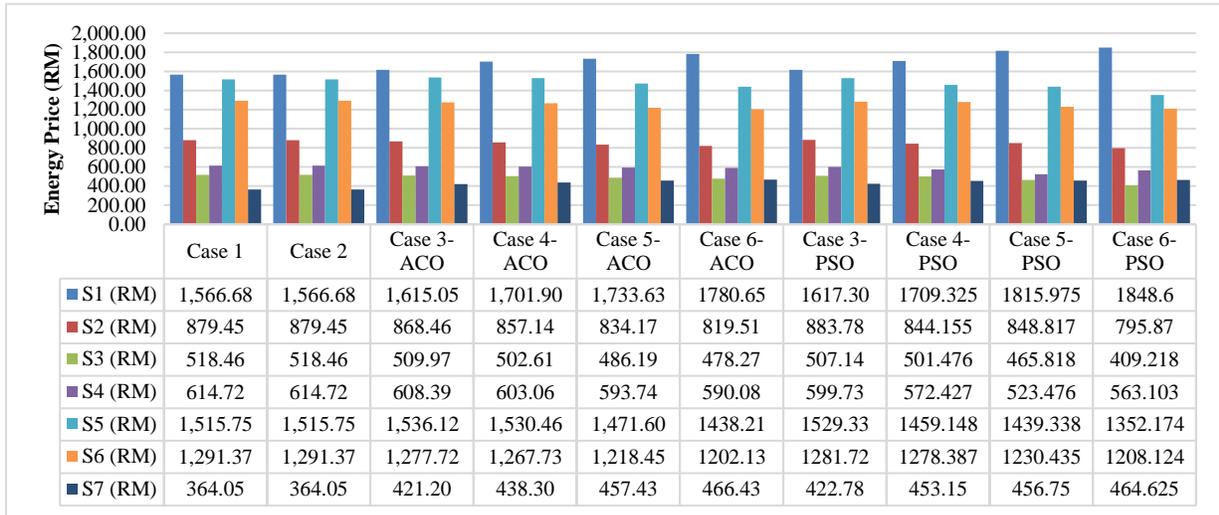


Fig. 6. Energy consumption cost of all segments.

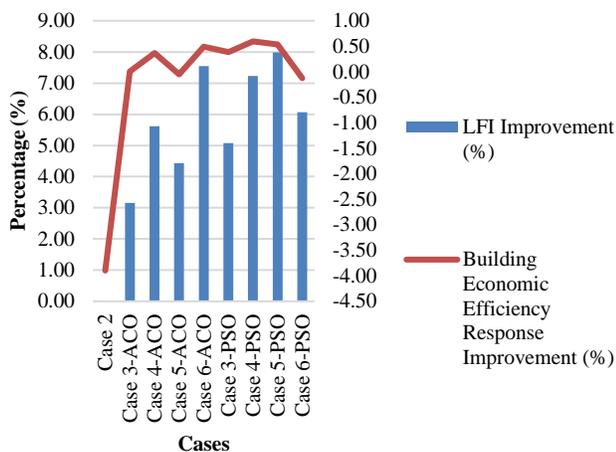


Fig. 9. LFI and BEERI improvement profiles.

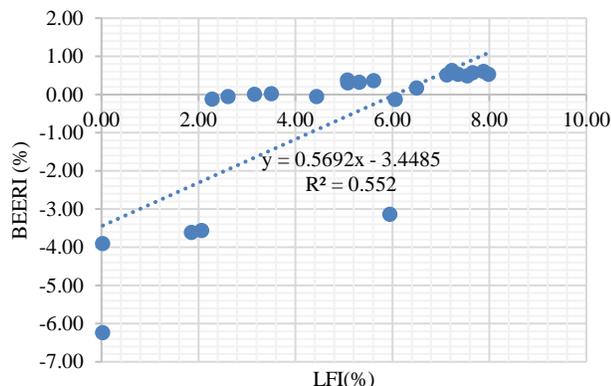


Fig. 10. LFI and BEERI correlation.

VI. CONCLUSION

Through the optimum formulation of the ETOU pricing for the industrial consumers, the effectiveness of it has been utilized well; wherever the simultaneous DSM's strategies able to manage the loads; at the same time mapping them to the ETOU price signal consequently. Since the six segmentation ETOU tariff's design in Peninsular Malaysia was different to others countries while the regulator has the authority to determine market conceptual; the proposed method to define the appropriate strategies for the electricity cost effectiveness from demand side consumers was presented well. By using the load apportioning technique in order to determine the controlled load to the implementation of the load management in adjusting weightage of 10% adjustable loads; the cost of the energy consumption (kWh) and maximum demand (kW) has been reduced properly. Most of the mid peak areas of MD location has contributed to the improvement of LFI while the relative component to determine the minimum percentage of load adjustment has been determined by using BEERI congruently. The performance of the both ACO and PSO algorithms has been analyzed while the ability of them to perform in the loads management environment has been considered succeed. Thus, the implementation of ACO algorithm has proven to be more sustained while produced better power consumption profile to be applied by consumer. After observation and analysis has been done, in order to enhance the topic of the study while open

for broad discussion in regards of the ETOU tariff pricing and cost optimization in consumer's side; there are several recommendation should be given attention:

- a) The needs of procedure for the load apportioning technique and tariff selection guidelines. Currently, we are using only details energy audit procedure but for the purpose of the economic view in determine most economic operation to be involved in load managements, it should be holistic consideration of guideline including risk management in industrial tariff selection.
- b) Future study of the impact of single DSM strategy to the simultaneous DSM strategies. The analysis of those strategies should be considered where the limitation on consumers' side to implement those strategies should be given attention. It also recommended to produce a proper technique for the optimum DSM strategies selection.

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REFERENCES

- [1] Y. Wang and L. Li, "Time-of-use based electricity cost of manufacturing systems: Modeling and monotonicity analysis," *Int. J. Prod. Econ.*, vol. 156, pp. 246–259, 2014.
- [2] M. E. Commission, "Briefing on Electricity Tariff Review in Peninsular Malaysia Incentive-based Regulation Regulatory Period 2 : 2018-2020," *Rep. RP1 Plan. RP2*, no. January, pp. 2018–2020, 2018.
- [3] Energy Commission (Malaysia), "Enhanced Time of Use (ETOU) Tariff Scheme Briefing Session with Key Stakeholders," 2015.
- [4] Malaysia Plastic Manufacturers Association, "Enhanced Time of Use (ETOU) Electricity Tariff Scheme Gradual Removal of Special Industrial Tariff (SIT)," 2017.
- [5] S. Ashok, "Peak-load management in steel plants," *Appl. Energy*, vol. 83, no. 5, pp. 413–424, 2006.
- [6] Z. Tan, M. Wang, J. Qi, J. Hou, and X. Li, "Time-of-use Price Optimizing Model And Fuzzy Solving Method," *Syst. Eng. - Theory Pract.*, vol. 28, no. 9, pp. 145–151, 2008.
- [7] R. S. Ferreira, L. A. Barroso, P. R. Lino, P. Valenzuela, and M. M. Carvalho, "Time-of-use tariffs in Brazil: Design and implementation issues," in *IEEE PES Conference on Innovative Smart Grid Technologies*, 2013, pp. 1–8.
- [8] S. Kwon, S. H. Cho, R. K. Roberts, H. J. Kim, K. Park, and T. Edward Yu, "Effects of electricity-price policy on electricity demand and manufacturing output," *Energy*, vol. 102, pp. 324–334, 2016.
- [9] G. Mordue, "Electricity prices and industrial competitiveness: A case study of final assembly automobile manufacturing in the United States and Canada," *Energy Policy*, vol. 111, no. April, pp. 32–40, 2017.
- [10] S. Tenaga, "Laporan Tahunan Suruhanjaya Tenaga 2016," 2017.
- [11] T. Y. Lee and C. L. Chen, "Iteration particle swarm optimization for contract capacities selection of time-of-use rates industrial customers," *Energy Convers. Manag.*, vol. 48, no. 4, pp. 1120–1131, 2007.
- [12] Y. Wang and L. Li, "Time-of-use based electricity demand response for sustainable manufacturing systems," *Energy*, vol. 63, pp. 233–244, 2013.
- [13] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1244–1252, 2012.
- [14] N. Kinhekar, N. P. Padhy, and H. O. Gupta, "Multiobjective demand side management solutions for utilities with peak demand deficit,"

- Int. J. Electr. Power Energy Syst.*, vol. 55, pp. 612–619, 2014.
- [15] A. Sepulveda, L. Paull, W. G. Morsi, H. Li, C. P. Diduch, and L. Chang, “A novel demand side management program using water heaters and particle swarm optimization,” in *IEEE Electrical Power & Energy Conference*, 2010, pp. 1–5.
- [16] H. Molavi and M. M. Ardehali, “Utility demand response operation considering day-of-use tariff and optimal operation of thermal energy storage system for an industrial building based on particle swarm optimization algorithm,” *Energy Build.*, vol. 127, pp. 920–929, 2016.
- [17] I. Aho, H. Klapuri, J. Saarinen, and E. Mäkinen, “Optimal load clipping with time of use rates,” *Int. J. Electr. Power Energy Syst.*, vol. 20, no. 4, pp. 269–280, 1998.
- [18] W. Xu, M. Zhou, H. Wang, and H. Liu, “A load management optimization approach considering economic efficiency and load profile,” *China Int. Conf. Electr. Distrib. CIGED*, vol. 2014-December, no. Ciced, pp. 907–911, 2014.
- [19] N. E. Mohammad Rozali, S. R. Wan Alwi, Z. A. Manan, and J. J. Klemesš, “Peak-off-peak load shifting for hybrid power systems based on Power Pinch Analysis,” *Energy*, vol. 90, pp. 128–136, 2015.
- [20] A. Abdulaal and S. Asfour, “A linear optimization based controller method for real-time load shifting in industrial and commercial buildings,” *Energy Build.*, vol. 110, pp. 269–283, 2016.
- [21] C. Li, X. Yu, W. Yu, G. Chen, and J. Wang, “Efficient Computation for Sparse Load Shifting in Demand Side Management,” *IEEE Trans. Smart Grid*, pp. 1–12, 2016.
- [22] J. Thakur and B. Chakraborty, “Demand side management in developing nations: A mitigating tool for energy imbalance and peak load management,” *Energy*, vol. 114, pp. 895–912, 2016.
- [23] E. Shirazi and S. Jadid, “Cost Reduction and Peak Shaving Through Domestic Load Shifting and DERs,” *Energy*, vol. 124, pp. 146–159, 2017.
- [24] N. A. M. Azman, M. P. Abdullah, M. Y. Hassan, D. M. Said, and F. Hussin, “Enhanced time of use electricity pricing for commercial customers in Malaysia,” *Pertanika J. Sci. Technol.*, vol. 25, pp. 285–294, 2017.
- [25] N. Azrina, M. Azman, P. Abdullah, M. Y. Hassan, and D. M. Said, “Enhanced Time of Use Electricity Pricing for Industrial Customers in Malaysia,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 6, no. 1, pp. 155–160, 2017.
- [26] M. F. Sulaima, N. Y. Dahlan, Z. M. Yasin, N. A. M. Asari, and Z. H. Bohari, “Optimum enhance time of use (ETOU) for demand side electricity pricing in regulated market: An implementation using evolutionary algorithm,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 8, no. 1, 2017.
- [27] N. N. Abu Bakar *et al.*, “Energy efficiency index as an indicator for measuring building energy performance: A review,” *Renew. Sustain. Energy Rev.*, vol. 44, pp. 1–11, 2015.
- [28] W. Tian *et al.*, “A review of uncertainty analysis in building energy assessment,” *Renew. Sustain. Energy Rev.*, vol. 93, pp. 285–301, 2018.
- [29] M. Dorigo, M. Birattari, and T. Stutzle, “Ant colony optimization,” *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28–39, 2006.
- [30] Marco Dorigo and Thomas Stutzle, “Ant Colony Optimization,” *Int. J. Comput. Sci. Netw. Secur.*, vol. 8, no. 6, pp. 351–357, 2008.
- [31] P. Stodola, J. Mazal, and M. Podhorec, “Parameter Tuning for the Ant Colony Optimization Algorithm used in ISR systems,” vol. 9, pp. 123–126, 2015.
- [32] K. Shweta and A. Singh, “An Effect and Analysis of Parameter on Ant Colony Optimization for Solving Travelling Salesman Problem,” *Int. J. Comput. Sci. Mob. Comput.*, vol. 2, no. 11, pp. 222–229, 2013.
- [33] K. Y. Wong, “Parameter tuning for ant colony optimization: A review,” in *International Conference on Computer and Communication Engineering*, 2008, pp. 542–545.
- [34] J. Kennedy and R. Eberhart, “Particle swarm optimization,” *IEEE Int. Conf. Neural Netw.*, vol. 4, pp. 1942–1948 vol.4, 1995.
- [35] Y. Shi, “Particle Swarm Optimization,” *IEEE Neural Networks Soc.*, no. February, pp. 8–13, 2004.
- [36] M. W. S. Engr. Majid Ali Member, Muhammad Fahad Zia, “Demand Side Management Proposed Algorithm for Cost and Peak Load Optimization,” *Smart Grid Congr. Fair (ICSG), 4th Int. Istanbul*, pp. 1–5, 2016.



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