DETERMINATION OF THE OPTIMUM LOAD PROFILE UNDER ENHANCED OF USE TARIFF (ETOU) SCHEME USING COMBINATION OF OPTIMIZATION ALGORITHMS AND SELF ORGANIZING MAPPING

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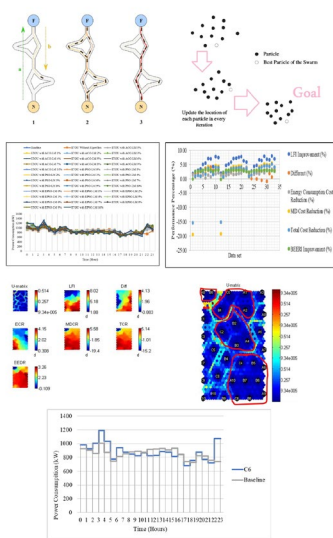[c]Faculty of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka (UTeM), 76100, Hang Tuah Jaya, Melaka, Malaysia
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Graphical abstract

Abstract

Demand side management (DSM) has been conventionally adopted in many ways to efficiently managing the appropriate electricity loads. However, with the sophisticated design of the Time of Use (TOU) tariff to reflect electricity cost reduction, implementing proper Load Management (LM) strategies is challenging. To date, consumers still struggle to define a figure for the LM percentage to be involved in the demand response program. Due to that reason, this study proposes a method to find the best load profile reflecting the new tariff offered by using a combination of optimization algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Evolutionary PSO (EPSO), and Self-Organizing Mapping (SOM). The evaluation has been made to the manufacturing operation with the existing flat tariff to be transferred to the Enhanced Time of Use (ETOU). The test results show that the ability of the proposed combination method to define the optimal outputs such as energy consumption cost, maximum demand cost, load factor index, and building electricity economic responsive index. Meanwhile, the SOM algorithm has been used to classify the enormous numbers of those simulation results produced by algorithms while defining the best LM weightage. As the test results for the case study, it was found that the practical 6% LM weightage was able to reflect the optimal required load profile shifting to be applied by manufacturing operation. Thus, by determining the optimal load profile that suits the ETOU scheme, the consumers can enjoy cost benefits while supporting the demand response program concurrently.

Keywords: Demand Side Management, Optimization Algorithms, Demand Response, Electricity Cost, Time of Use Tariff

1.0 INTRODUCTION

In Malaysia, Demand Side Management (DSM) through Demand Response (DR) program has been mainly introduced in terms of tariff initiatives such as Enhanced Time of Use (ETOU) scheme. The scheme has been offered to commercial and industrial consumers since 2015. However, As reported by [1], only a small number of consumers are willing to join the ETOU program in Malaysia. At the same time, the rest of the consumers are less interested due to a lack of knowledge in load management, guidance, and references from the expert. There are references related to the ETOU formulation and optimization studies in Malaysia, for example, [2], [3]. Still, again only load shifting strategies have been analyzed as no optimization algorithm is involved to prove this concept. The optimal ETOU cost and load shifting strategies are also

presented in [4], [5] which proposed the application of algorithm such as Evolutionary Algorithm and Particle Swarm Optimization. Meanwhile, the connection of those DSM strategies to the initiative of the tariff program such as time of use regime was touch so that the effectiveness of the demand response program to the consumers' electricity cost reduction is not tremendous. Thus, recent reference as in [6] closed this gap where the appropriate strategies of DSM such as valley filling, peak clipping and load shifting have been applied concomitantly in a load profile. A robust algorithm is formulated to optimize the electricity cost in reflecting the newly introduced tariff regime, the Enhanced Time of Use (ETOU), specific to the peninsular Malaysia electricity energy market.

Other references to date that determine the optimal energy cost for related work under price-based program reflecting the TOU tariff are given in [7]–[14]. The machineries scheduling in manufacturing based on demand response program and reflecting the TOU tariff pricing have been well explained. Optimum operation strategy and scheduling towards a sustainable cost benefit regarding electricity consumption to the amount of production output have been considered when the load management is applied. Furthermore, the differential of the time segmentation in TOU program such as the low price at off peak hours has been given attention by tariff designers where coordination of them should reflect the ability of the consumers to apply the load management. Nevertheless, during setting up the load management weightage to be involved in using LM strategies, there is no method so far that can be applied to define its optimization.

Therefore, this study proposed an investigation to determine the optimal load profile under the ETOU tariff scheme, which applies the Ant Colony Optimization (ACO), PSO and Evolutionary PSO (EPSO) 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 [17]. 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 [18]. ACO is selected in this study because it performs a model-based search and is similar to estimating distribution algorithm [19]. In conjunction with that, the PSO introduced by Kennedy and Eberhart [20] will be the baseline performance algorithm to compare with ACO algorithm performance. Meanwhile EPSO was proposed to search for the better convergence as to improve the performance of PSO algorithm.

On the other hand, classification technique has been applied in various objectives for decades in this area of DSM study. In [15], the authors proposed the hierarchical clustering method to be performed on the historical data of energy profile where decision makers will be able to apply DSM strategy or automate the demand response in response to the forecast energy profile for the next day. In conjunction with the application under the DSM program on top but for energy efficiency program priority to be implemented in huge education buildings, the classification technique has been proposed by [16] using K-means clustering method. In the other example, the clustering method has been applied on different objective which is clustering the behavior of the consumers in six categories of attributes under the DSM program [17], where K-means clustering technique has been used to manage the data of this survey. The classification technique performed well to create a brief idea for the output of the energy saving behavior. Still, the additional future attribute involved would be better than other modification clustering techniques as suggested by [18], [19].

In other application of clustering technique, Self-Organizing Map (SOM) is more reliable to be conducted when dealing with big data in supporting DSM program. SOM principle has been used extensively as an analytical and visualization tool in exploratory data analysis [20]. The SOM models are associated with the nodes of a regular, usually two-dimensional grid, as presented in [21], who upgraded the latest version which is available in [22]. Since SOM application is new in this field of study, there is a lack of reference for SOM implementation relative to the LM strategy. For example, in [23], SOM has been applied to classify residential load profile from a huge electricity data into 10 classes. Load characterization will help utilities to design a good tariff that satisfies both consumers and generating companies. In addition, SOM algorithm has been utilized in [24] to estimate the load profile in deregulated electricity market. The result shows that SOM can reduce load demand forecasting errors to lower than 3% compared to the conventional method. In applying the new technology, SOM has been used to determine the appropriate sizing and location of Distributed Generation (DG) [25], which has contributed to reducing power losses in the power system while securing the ability of the power supply without any interruption. After reviewing many references for the classification technique, the superior algorithm selected for this study's purpose is the Self-Organizing Map (SOM). In this case, SOM clustering can also be considered to interpret better results regarding searching and mapping aspects in reflecting to the price-based program. To date, SOM implementation in this area of research is still scarce, which implies that there are room for utilization of SOM in determining the optimal consideration especially for the study under DSM program. Based on the above brief literature review, it is palpable that the load management related to DSM program has been tackled by a number of researchers involving various objectives, method and implementation. Therefore, the present study aims to fill the gap and supplement research in literature on the under LM strategy while seeking to optimize its operational to determine the best load profile pattern for ETOU tariff consumers.

The proposed study presents a unique computational solution framework of an optimal results find to reflect electricity tariff offer by utility using combination of artificial intelligence technique. Thus, the contribution of this paper can be described as following: 1) A method to find the optimal load profile under electricity ETOU tariff scheme by using combination of optimization algorithms (PSO, ACO and EPSO) and Self Organizing Mapping (SOM). Combination results of those adopted algorithms are able to present the best load profiles while ensuring that consumers are eligible to enjoy the electricity cost saving when switching to ETOU tariff. 2) The propose classification technique to be combined in the process of searching for the best solution able to best load management weightage so that consumers able to set the action for load management with minimum system arrangement. Various simulation outputs before load

management implementation will be classified and mapped into other forms so that the optimum of consumer's load profile may be selected consequently.

The paper has been arranged as following: Section 2 presents load management formulation while Section 3 explain the optimization methods. Meanwhile, Section 4 presents results and analysis of the study. Finally, the conclusion will be in Section 6.

2.0 METHODOLOGY

2.1 Load Management Formulation

2.1.1 ETOU Tariff Scheme

The ETOU tariff is expressed in terms of cost unit where the objective function is to minimize the energy consumption and MD costs. The optimal total ETOU electricity cost (MYR) can be written as:

$$ETOU_{cost}^{optimal} = ETOU_{eCost} + MD_{Optimum\ allocation}^{Cost} + ETOU_{eCost\ Wk/P}$$

(1)

where $ETOU_{eCost}$ is the electricity consumption cost of the desired load curve after the LM strategies are implemented, which reflects the base price of the six-time segments as in Eq. (2). The arrangement strategy to mitigate the MD cost, MD_{MP}^{Cost}, and optimize allocation is presented in the Eq. (3). The charge for $ETOU_{eCost\ Wk/P}$ is the total energy consumption cost for the weekend, which is a constant in this study.

$$ETOU_{eCost} = \min \sum_{hour\ i=1}^{N} P_{total\ power\ consumption} \times TP_{ETOU})$$
$$= (\sum_{hour\ i=1}^{10} P_{op} \times TP_{op}) + (\sum_{hour\ i=1}^{3} P_{mp1} \times TP_{mp})$$
$$+ (\sum_{hour\ i=1}^{1} P_{p1} \times TP_{p}) + (\sum_{hour\ i=1}^{2} P_{mp2} \times TP_{mp})$$
$$+ (\sum_{hour\ i=1}^{3} P_{p2} \times TP_{p}) + (\sum_{hour\ i=1}^{5} P_{mp3} \times TP_{mp})$$

(2)

N is total number of the loads P_{op} is optimum power consumption in the off-peak zone (desired load curve) with respect to $hour\ i = 1$, (the different of base power consumption and the changing of consumption, ΔP_x). Meanwhile, P_{mp1}, P_{mp2}, P_{mp3} is optimum power consumption in the mid-peak zone (desired load curve) with respect to $hour\ i = 1$. (the different of base power consumption and the changing of consumption, ΔP_x). And, P_{p1}, P_{p2} is the optimum power consumption in the peak zone (desired load curve) with respect to $hour\ i = 1$ (the different of base power consumption and the changing of consumption, ΔP_x) TP_{op}, TP_{mp}, TP_p are the utility ETOU tariff price for off-peak, mid-peak and peak time zones, respectively. The MD charge is given by:

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

(3)

The MD charge is vital in calculating the total electricity cost. In this study, $MD_{Optimum}^{cost}$ was set as the variable for $ETOU_{min}^{cost\ saving}$, as indicated by Equation (2). For this reason, it is necessary to select the optimal MD and allocation at the

exact time segment. The selection of the optimal power load for the MD charges at the mid-peak and peak loads are presented in Equations (4) and (5), respectively. Equation (6) shows the optimum MD charge $MD_{Optimum\ allocation}^{Cost}$ obtained by sorting the MD charges at the mid-peak and peak loads.

$$MD_{MP}^{cost} = \max[L_{T2}; L_{T4}; L_{T6}] \times MD_{MP}^{TP}$$

(4)

$$MD_{P}^{cost} = \max[L_{T3}; L_{T5}] \times MD_{P}^{TP}$$

(5)

$$MD_{Optimum}^{Cost} < MD_{P}^{cost}, MD_{MP}^{cost} \in MD_{Optimum}^{Cost}$$

(6)

Where, MD_{MP}^{cost} is an optimum price of power load selection in the mid-peak area while MD_{P}^{cost} presents the optimum price of power load selection in the peak area. L_{Tn} is the selected power load for n number at a particular time segment ts. Meanwhile, MD_{MP}^{TP} and MD_{P}^{TP} is MD charge for mid-peak and peak loads, respectively

2.1.2 Simultaneous Load Management Strategies

In this study, Load Shifting, Valley Filling and Peak Clipping have been selected as the load management strategies in optimizing the load profile. Simultaneous formulation of those strategies is demonstrated in Eq. (7) accordingly.

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

(7)

Where $\Delta P_{ts,i}^{VF}$, is the change in the desired load based on valley filling technique at random load (i) in time segmentation (ts). $\Delta P_{ts,i}^{PC}$ and $\Delta P_{ts,i}^{LS}$ are the change in the desired load based on the peak clipping and load shifting technique at random load (i) in time segmentation (ts), respectively. In order to define the limitation of the reported controlled load available at consumers' side, the lower bound and upper bound of the random load setting selection (i) has been set as in Eq. (8). In addition, the minimum order for the controlled load is set to 0.5% while the maximum order of it is 10% to follow the identified controlled percentage available by consumers.

$$0.005 \leq i \leq 0.10$$

(8)

Temporarily, WVF, WPC, and WLS are the weightage used in every single load profile concurrently; which is set by consumers depending on the percentage of the load weightage setting at particular time segmentation, this is depends on the finding of the controlled load available to be involve in load management. This weightage will be classified into several cases due to the changes that affect the valley filling ability, peak clipping and load shifting technique in reflect to the optimization algorithm. Apart from that, the constraints of the load management strategies to achieve satisfying performance have been decided as follows:

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

$$\text{Average load price} > \Delta P_{ts,i}^{VF} \geq \text{Min base load price} \tag{9}$$

b.   Constraints for peak clipping

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

$$\text{Average load price} < \Delta P_{ts,i}^{PC} \leq \text{Max base load price} \tag{10}$$

c.   Constraints for load shifting

Load shifting leads to perform at randomly selected three-time segmentations when dealing with ETOU tariff regime which consists of six segmentations. The best way to put load shifting is after valley filling and peak clipping selection, while the rest of the time segmentations will be the location for load shifting to perform randomly. Equation (11), Equation (12) and Equation (13) demonstrates load shifting process, accordingly.

$$\Delta P_{ts,i}^{LS} \cong \Delta Z_{ts,i}^{shift} \tag{11}$$

$$\Delta Z_{ts,i}^{shift\ down} = \left(\Delta Z_{up}^{shift} - \left(\left(\Delta Z_{up}^{shift} - \Delta Z_{down}^{shift} \right) \times \omega \right) \right) \tag{12}$$

$$\Delta Z_{ts,i}^{shift\ up} = \left(\Delta Z_{up}^{shift} - \left(\left(\Delta Z_{up}^{shift} + \Delta Z_{down}^{shift} \right) \times \omega \right) \right) \tag{13}$$

Where, ΔZ_{down}^{shift} demonstrates changing of load (decreases) at certain time segmentation (*ts*) for the load, *i*; ΔZ_{up}^{shift} represents changing of load (increases) at certain time segmentation (*ts*) for the load, *i*; and ω is the random weightage of load decrease and increase at lower bound and upper bound load setting as Eq. (8). Since the load management strategy has been explained in [6], this study follows the same six segmentation formulation so that all the constraints setting included for the Maximum Demand should be adjusted to Mid Peak and Peak zones and the energy consumption before and after simulation should be not far different. Load Factor Index (LFI) has been adopted as shown in Eq. (14).

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

Where, $\sum E_{TSn}$ is the total electricity consumption for total *n* time segmentations, and *t* is time of electricity usage; while $MD_{Optimum}^{kW}$ is the optimum selection of MD (kW) at peak or mid peak zones. Meanwhile, Eq. (15) represents the most correlated performance of load management indicator: Building Electricity Economic Responsive Index (BEERI). In BEERI, the priority concern is to overlook and standardize the correlation of maximum demand cost optimization and energy cost optimization to the impact of total electricity cost, respectively.

$$BEERI = \frac{MD_{Optimum}^{Cost}}{ETOU_{cost}^{optimal}} \tag{15}$$

2.2 Optimization Method

2.2.1 Ant Colony Optimization (ACO)

The ACO algorithm on the six segmentation of ETOU tariff mechanism has been implemented in [4]. In this study, a similar technique has been applied but using simultaneous LM strategies. The flow of the ACO process to find the optimal solution is similar. The summary steps for the ACO algorithm that has been applied in this study are as follows:

Step-1: The ants represent a set of possible initial load profiles to determine a single 24-hour change in each electricity energy cost, known as nodes. The fitness values will be used for updating and gathering more ants to proceed to the next step. To ensure the effectiveness of the desired optimum output, initialization process is maintained as tariff structure in Eq. (1) is called, and all the constraints as in Eq. (8) until (13) are applied strategically.

Step-2: Formulating the constraints and determining the cost. The updated pheromone values will be used to formulate the optimal ETOU electricity energy cost as MD cost. The updated energy consumption cost (Eq. (2)) and MD cost (Eq. (3)) in six-time segmentation will be used as the best cost value in ACO process, and then proceed in determining the updated ants pheromone accordingly.

Step-3: The best total energy cost for all segmentations is determined by the best cost value during pheromone update, while the best ants to symbolize optimal load profile is created concurrently

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. 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 energy consumption cost and MD cost on the contribution of LFI (Eq. (14)) and BEERI (Eq. (15)) is generated.

2.2.2 Particle Swarm Optimization (PSO)

The stage of implementation by using PSO algorithm in determining optimal power energy consumption profile is as follows:

Step 1: Initialization. The process starts with the initialization of the population, which is determined by calling the load profile in a 24-hour pattern. Those variables are generated randomly while PSO parameters are then initialized, such as number of particles N, weighting factors, C1 and C2, and the maximum number of iterations. In order to ensure the effectiveness of the desired optimum output, initialization process is maintained as tariff structure in Eq. (1) is called, and all the constraints as in Eq. (8) until (13) are applied strategically.

Step 2: Fitness Calculation. For the particles that fulfills the constraints as in Step 1, the load profile will be analyzed while the optimal ETOU energy consumption and maximum demand costs are produced simultaneously using Eq. (2) and Eq. (3). Meanwhile, the input of the calculation and constraints is used to calculate the load factor improvement and building electricity economic responsive index as formulated in Eq. (14) and (15).

Step 3: Determine Pbest and Gbest. During the searching process, the two best values are updated and recorded. The Pbest and Gbest represent the generation of best energy

consumption cost as well as generate the optimum MD cost synchronously.

Step 4: New Velocity and Position. In this process, the particles' velocity and position is updated by applying Equation (16) and Equation (17), 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 then repeated.

$$V_j^{k+1} = \left(\omega \times V_j^k\right) + \left(C_1 r_1 \left(P_{best\,j}^k - X_j^k\right)\right) + \left(C_2 r_2 \left(G_{best\,j}^k - X_j^k\right)\right) \tag{16}$$

$$X_j^{k+1} = X_j^k + V_j^{k+1} \tag{17}$$

Where, V_j^κ is velocity of particle j in iteration. k. X_j^κ is position of particle. j in iteration k with ω presents inertia weightage. The best value of fitness function that has been achieved so far by particle j in iteration k is presented by $P_{best\,j}^\kappa$. Meanwhile, the best value among the fitness values is prompted by $G_{best\,i}^\kappa$. The constants C_1 and C_2 represent weightage factor of random acceleration terms while $V_j^{\kappa+1}$ and $X_j^{\kappa+1}$ demonstrate the new velocity and new position, correspondingly.

2.2.3 Evolutionary Particle Swarm Optmization (EPSO)

EPSO has been proposed to solve issues in power system such as optimal the distributed generation sizing and allocation such to minimize the distribution losses [26], [27]. It is inspired by the hybridization of basic PSO and Evolutionary Programming, an adaption of the combination and selection process prior to Step 4 of PSO algorithm technique. Before Equation (16) and Equation (17) are called, the EPSO method is combined to generate the set of global best candidates to be tested in a tournament step, where the results of load profiles are reflected as the best optimum energy cost after it has been combined and selected concurrently. Thus, the final decision as well as convergence process will follow Step 4 of PSO algorithm accordingly.

2.2.4 Optimal Load Management Weightage by using Self-Organizing Mapping (SOM)

In this study, unlike focusing on the input data of the supplier and forecasting technique on the consumers' energy profile such as in [28], the direction of the paper has succeeded in clustering the input data from multiple results of optimization simulation such as load factor improvement, differential, energy cost reduction, maximum demand cost reduction, total cost reduction and building electricity economic for demand response to perform the best matching unit (BMU) in the output space of SOM. Many factors contribute to a good energy consumption profile where varieties of data are difficult to understand and analyzed. For this reason, the SOM is used to classify and cluster the group of the data output to ensure that the reader could understand which percentage of the load management weightage is optimum for their demand side management program. In the context of SOM, the number of neurons may vary from small numbers to multi millions. A dimensional weight vector has been introduced to represent the neurons in the input vector. The steps required for the SOM implementation are as outlined below:

Step-1: All percentage values of the desired inputs are to be called by SOM algorithms in space of neuron inputs layer. The values arise from three algorithms performance as explained before. The cases of the load management adjustment's percentage are recorded while reduction or increment of the desired results in percentage value are recorded simultaneously

Step-2: The correlation of the data input in the SOM process is connected to each other known as the neighborhood relation represented by its topology. In this step, SOM is endangered to iteration for training network as other algorithms function. Meanwhile, there exists a sample vector 's' at input data from each iteration selected randomly; by which distances of the data nodes are produced by particular distance measures simultaneously.

Step-3: In this step, the BMU formula, as in Eq. (8), is introduced where the input data of the energy cost related to the results from those algorithms in multidimensional layer that have the closest weight vector to sample vector 's', as in Step 2, has been presented by 'c', where 'c' denotes the Euclidean distance measure.

$$\| s - mc \| = min_i \| s - m_i \| \tag{18}$$

Step-4: In this step, the SOM weight vectors are updated so that the presented BMU are moved to be closer than before. This process happens in the input data space. Through this process, BMU and its neighboring topology is stretched out towards the sample of vector. Thus, the updating process of the BMU, as demonstrated in Eq. (19), occurs accordingly. Here, 'm' represents the weight of the vector in unit i, 't' represents the time, s(t) is a random selected input vector from the set of input data at time t, hci(t) is the neighborhood kernel around winner c, while α(t) is the learning rate at time t. The neighborhood kernel defines the region of influence that the input sample has on the SOM. In this step, the topology of the output space in two-dimensional layer is created where various data are mapped and clustered congruently.

$$m_i(t + 1) = m_i(1) + a(t)hci(t)[s(t) - m_i(t)] \tag{19}$$

In the setting up of SOM as described in the steps of SOM process, the simulation is taken from the combination of various normalization method such as 'var', 'range', 'log', and 'logistic' to the setting number of min and max value of neurons. In this exercise, the study decided to follow the min number of neurons as in [29], but extend the max value to 400 neurons to determine better selection results in the framework of demand response and performance of the load management weightage clustered and mapped. It is normalized to unity and means to zero for data input of 'var' data normalization. The 'range' input data has been normalized from zero to one. However, different from the other normalization methods, the

'log' data input has been normalized using Eq. (20), the natural logarithm equation.

$$X_{new} = \log(X - m + 1)\, ; m = \min X$$

(20)

Meanwhile, for the normalization method of 'logistic', the scale of it considers all the possible values between zero to one.

3.0 RESULTS AND DISCUSSION

The cases are divided into three major groups to reflect each of the optimization algorithms, while the percentages of load management setting are presented in the sub-cases. The real peninsular Malaysia current electricity tariff for the industrial E1 and ETOU pricing is applied to get outputs of the study. Meanwhile, for the analysis of the load management weightage, the arrangement of the cases for this study are set as follows:

a) Case 1: Baseline of the existing E1 flat tariff rate.
b) Case 2: E1 ETOU tariff rate without any DSM Strategies and algorithm.
   i. Case As: E1 ETOU tariff rate by using (load weightage: A0=0%, A1=1%, A2=2%, A3=3%, A4=4%, A5=5%, A6=6%, A7=7%, A8=8%, A9=9%, A10=10%) of the DSM Strategies and ACO algorithm implementation.
   ii. Case Bs: E1 ETOU tariff rate by using (load weightage: B0=0%, B1=1%, B2=2%, B3=3%, B4=4%, B5=5%, B6=6%, B7=7%, B8=8%, B9=9%, B10=10%) of the DSM Strategies and PSO algorithm implementation.
   iii. Case Cs: E1 ETOU tariff rate by using (load weightage: C0=0%, C1=1%, C2=2%, C3=3%, C4=4%, C5=5%, C6=6%, C7=7%, C8=8%, C9=9%, C10=10%) of the DSM Strategies and EPSO algorithm implementation.

3.1 Optimization Performance

Comprehensive energy profiles that were produced in the manufacturing energy consumption are presented in Figure 1 accordingly. It was observed that most of the loads were moved to the significant direction either vertically or horizontally. The movement of the load arrangement is mapped to the significant DSM strategies which were Peak Clipping (PC), Valley Filling (VF) and Load Shifting (LS) performance simultaneously as presented by [6]. For instance, VF strategy from 23:00pm to 24:00pm changed dramatically, increasing approximately 427kW or 36.52%.
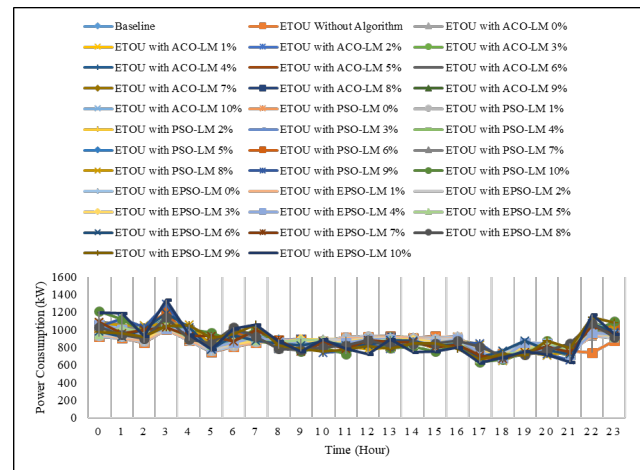

Figure 1 Energy Profile for all cases

Thus, in order to acknowledge the performance of the proposed LM strategy and its integration on three implemented algorithms (ACO, PSO and EPSO), we present the 6 categories of the significant percentage result performance as in Figure 2. It is observed that the tabulated data increased in terms of respective performance especially for the LFI where most of the algorithms' performance achieved more than 5% improvement. For the results in terms of the cost reduction (energy consumption cost, MD cost and total electricity cost), the ranges of percentage saving were between 0.1% to under 5%. It implies that most cases under the three algorithms contributed to reduce the related cost of electricity for all considerations. However, there were insufficient results noticed for 0% weightage load management of Case A0 and Case B0. Both performance of MD cost reduction and total electricity cost reduction were negative. Correspondingly, there were losses of electricity cost for approximately 15% to 19% for MD and total bill. It is analyzed that the correlation of the MD cost to the total electricity cost is significant in defining the performance of all cases. In terms of individual energy consumption, cost reduction performance PSO result of Case B7 produced the best result among all, meanwhile for EPSO Case, for instance Case C10, produced better reduction percentage which was average of roughly above 5%. On the other hand, total electricity cost was produced by 9% of load management weightage which was observed to be the highest, presented by Case C9 accordingly. Nevertheless, it was noticed that the ACO Cases recorded better results in terms of economic efficiency for DR impact improvement compared to another algorithm performance.
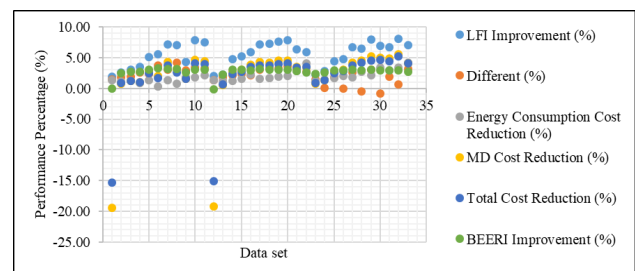

Figure 2 Tabulated data for SOM input process

3.2 Clustered and Mapping

Due to the various topology of the results performance among ACO, PSO and EPSO algorithms; the Self Organizing Mapping (SOM) algorithm was used to select a better performance result and determine the right load profile to be proposed to consumers. In this study, data normalization for those methods has requested to produce maps. It also presents the high value of controlling the map topology, which at the same time hides other components. It was observed that all four normalization methods achieved minimum quantization and topographic error at different number of neurons; given by 'var'-400, 'range'-360, 'log'-380, and 'logistic'-380. Errors in the tables indicate the stability of the achievement through hexagonal lattice where small value of errors represent optimum classification and selection results. On the other hand, it is observed that the training time for all the neurons' number were less than 6 seconds, where lesser time is taken for the training process. Here, minimum value of errors refers to better mapping capability and quality of the classification and selection. As the relationship of the methods are compared, it was analyzed that the best quantization error, topographic error and the training time for the mapping process goes to the 'logistic' method as presented in Table 1. The optimum classification and selection of the input data was performed when 380 neurons converge during only 5 seconds, where the quantization error was recorded at 0.001 and the value of the topographic error was 0.000. It was the best achievement so far for the set of the objectives in this area. Upon comparing it with other objectives of the study, the obtained results were better than [29], [30], [31].

Table 1 'logistic' normalization method convergence errors and training time in hexagonal topology

No. of Neurons	Map Size	Quantization Error	Topographic Error	Training Time (s)
120	[15,8]	0.034	0.000	1
140	[16,9]	0.030	0.030	1
160	[16,10]	0.025	0.030	1
180	[18,10]	0.018	0.000	2
200	[18,11]	0.014	0.000	2
220	[20,11]	0.013	0.000	2
240	[20,12]	0.011	0.030	3
260	[22,12]	0.008	0.030	3
280	[22,13]	0.008	0.000	3
300	[23,13]	0.008	0.000	3
320	[23,14]	0.003	0.000	3
340	[24,14]	0.003	0.030	4
360	[25,14]	0.003	0.030	5
380	[25,15]	0.001	0.000	5
400	[27,15]	0.001	0.000	7

Apart from that, by referring to Figure 3, there are six planes that have been analyzed to be the features of the U-matrix mapping. It consists of the percentage of improvement for Load Factor Index (LFI), Different (Diff) of energy consumption before and after simulation, Energy consumption Cost Reduction (ECR), MD Cost Reduction (MDCR), Total electricity Cost Reduction (TCR) and Efficient Economic Demand Response (EEDR). The topology of LFI, Diff, ECR, MDCR, TCR and EEDR was formed in different scale of consideration while it was noticed

that the correlation between MDCR and TCR is significant in influencing the EEDR character. This implies that, the cost of maximum demand to the total cost of electricity for the case study has contributed to determine the value of economic efficiency for the demand response program. The references for the planes portrayed that the darkest color represents the lowest value while the lightest color reflects the highest value obtained. For the rest of the other planes such as LFI, Diff and ECR, it was observed that each component draws a different pattern to present the uniqueness of the numerical features. Thus, those planes selected in this study showed their specialization in influencing the U-Matrix topology and classifying the input data to produce better map characteristics. As a result, it was easy for us to analyze the U-Matrix and select the best group to be considered the best performance technique with minimum weightage of load management.
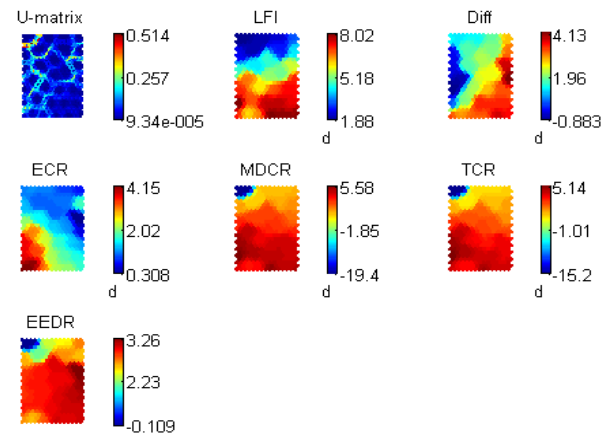

Figure 3 Six components of planes that represent numerical calculated features

3.3 The U-Matrix Classification and Best Load Profile

In this study, the hexagonal topology is used to perform the U-matrix pattern instead of other available topology; for instance, the rectangular condition requires a smaller number of neurons and small input data to achieve low quantization errors. The U-matrix generated by the simulation of the stated input data LFI, Diff, ECR, MDCR, TCR and EEDR was the best topology selected during the four-normalization method comparison. The best result of the normalization with minimum errors was the 'logistic' and its U-matrix topology is presented in Figure 4, accordingly. It is considered that the accuracy of the classification movement in U-matrix topology via BMUs is precise with the ability to produce good mapping quality. The map in U-matrix is decided to be grouped in four groups based on the clustering process. The border of lighter color is determined to be the partition for the selection of results data produced by the three algorithms in significance of four clear groups in the U-matrix. Meanwhile, other individual and dual broader groups were neglected. The clear and darkest group selection is presented by the result of the lowest scale value in the U-matrix. Thus, in further discussion of the results analysis, the SOM selected results were compared and elaborated in Table 2, accordingly.
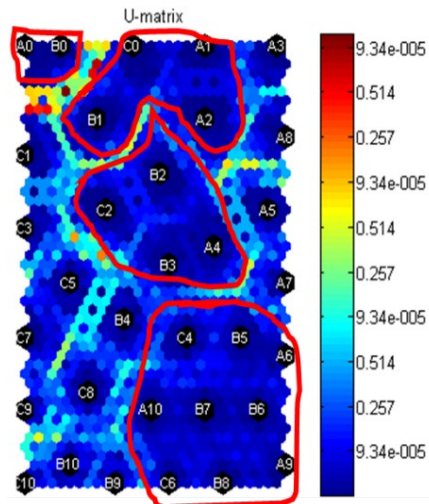
Figure 4 U-matrix for the 'logistic' normalization method with minimum errors and optimal convergence time

Table 2 Classification results for the group selection of U-matrix observation

Classification	Groups Selection
Not perform (with adjustment but worse results for certain consideration)	A0, B0
Fast response performance (Min Weightage of Load Management with good results)	A1, A2, B1, C0
Intermediate performance (middle of load management weightage with good results)	A4, B2, B3,C2
Maximum performance (huge adjustment of load management weightage with superior results)	A6, A9, A10, B5, B6, B7, B8, C4, C6
Optimum Performance (adjustment of load management with superior results)	A9, B8, C6
Optimal Load Profile (minimum LM weightage and balance results to all outputs)	C6

Therefore, in this study, case C6, the EPSO algorithm implementation, is selected to present the best load pattern that the manufacturer should apply to enjoy sustainability and secure the ETOU tariff transform. This implies that by utilizing a minimum adjustment of load, roughly 6% from the selected controlled load, the electricity's optimum cost in reflect the price-based program would be achievable. The proposed load curve for load management within a 6% controlled load adjustment environment is presented in Figure 5. As the adjustment for certain system operation is required, the load movement that adopts the simultaneous LM strategy could be concluded as the backbone for the better achievement of results in this study.
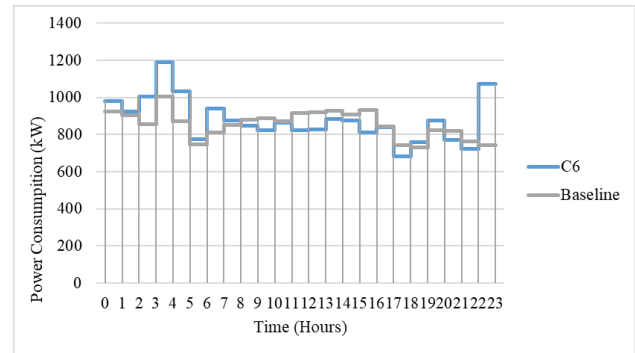

Figure 5 Load curve of C6 Case for the optimal solution

4.0 CONCLUSION

This study presents a dedicated and practical concept of searching for the best load curve to reflect the price-based program. The proposed method has significantly contributed to defining the best load profile for the manufacturing consumer to join the ETOU scheme. Meanwhile, the optimization algorithms with presented load management formulation and constraints have lowered the utility bill. The findings of this study proved that, by highlighting the consumer's minimum load management weightage as controlled load, the consumers with the new tariff scheme could successfully conduct the demand response program. The optimization algorithm such as ACO, PSO, and EPSO has been usefully involved in this procedure. The hybrid algorithm like EPSO has given good performance in searching for the optimal load profile reflecting price signal from the ETOU tariff. Meanwhile, the SOM algorithm performs to cluster most cases to a better condition and environment where a perfect load profile with optimum weightage of load management has been selected at the end of the study. Hence, the output of this study would be benefited to the energy manager while the study's method can be a good value for the body of knowledge. Future research could be extended to explore the relationship between energy efficiency action that could support demand response programs to be executed well in the building's operation.

Acknowledgement

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