



OPTIMAL COST BENEFIT OF THE ETOU ELECTRICITY TARIFF FOR A MANUFACTURING OPERATION BY USING OPTIMIZATION ALGORITHM

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ABSTRACT

Since the electricity market are getting more attention due to the electricity demand, there are many options of tariff can be chosen thus making it harder for consumers to make decisions. The consumers must be searching for affordable tariff rate that able to give the benefit in reducing the total electricity cost. In regard to the issue, Tenaga Nasional Berhad (TNB) has introduced a more advanced tariff under Demand Side Management (DSM) programs namely Enhance Time of Use (EToU) tariff as an advanced version of the Time of Use (ToU) tariff for generation and demand side benefits. However, the number of participants has joined the program is under expectation due to less awareness and knowledge on the demand side management strategy. Thus, in this study, Simultaneous Demand Side Management (DSM) strategies are proposed for energy consumption cost reduction for a manufacturing energy load profile. Optimization algorithm namely Ant Colony Optimization (ACO) is implemented and cases with and without implementation of algorithm are compared in order to idealize the load profile of DSM strategy. The proposed method had shown reduction in electricity cost at all time zones of EToU tariff. The final result of this study is hopefully will contribute to help the industrial consumers in managing their tariff selection and to make demand side management program more acknowledgeable to the consumers.

Keywords: time of use (ToU), enhanced time of use (EToU), demand side management (DSM), ant colony optimization (ACO).

1. INTRODUCTION

The increasing demand in electricity consumption are gathering concern due to the continuous energy generation from burning fossil fuel that has led to the increasing of CO₂ emission [1]. It was reported that 84% of CO₂ emissions are because of manufacturing activities [2]. Demand-side management (DSM) programs has been introduced in order to provide solutions to these issues and to promote and regulate energy efficiency in Malaysia and Time of Used (ToU) tariff scheme has been introduced by Tenaga Nasional Berhad (TNB) in 2014 under these programs.

After the implementation of the tariff, there have been an upsurge in electricity price. To overcome this issue, TNB has introduces a new more advanced tariff scheme known as Enhance Time of Use (EToU) for industrial consumer in 2016. EToU tariff main objective is to promote demand side management through peak load reduction that can leads to electricity expenses reduction. However, it is reported that only 1% of commercial and industrial consumers join the program [3].

Many past studies have been conducted on ToU and EToU tariff. In [4], a ToU tariff design has been developed from a flat tariff to save electricity cost by using DSM strategies, but the study is focusing on designing the new tariff. The ToU tariff rate was designed by using a clustering technique, namely Gaussian Mixture Model. Authors in [5] used a stochastic-based decision-making framework to optimize the electricity portfolio and ToU pricing as well as to maximize the profit and

minimizing the risk for retailers. In [6], the impact of the EToU tariff scheme has been analyzed by analyzing two different industrial consumers load profile to come out with the advantages of EToU tariff in order to help customers choosing between ToU and EToU tariff scheme. Meanwhile, in [7] and [1], optimization algorithm (ACO algorithm) and optimal EToU tariff formulation have been used to optimize the uptight load profile of a DSM strategy to reduce the electricity cost based on EToU tariff.

There were past researches that use Ant Colony Optimization (ACO) algorithm to solve problems involving the load demand and electricity price. A mutated operator integrated ACO scheduling scheme has been proposed to minimize electricity consumption cost while reducing the drawback of original ACO has been proposed in [8]. In [9], an algorithm for energy management system (EMS) based on multi-layer ant colony optimization (EMS-MACO) is presented to analyze energy scheduling in Microgrid (MG).

In this study, the Simultaneous Demand Side Management (DSM) strategies are proposed for energy consumption cost reduction for a manufacturing energy load profile. Optimization algorithm namely Ant Colony Optimization (ACO) algorithm are implements and cases are compared in order to idealize the load profile of DSM strategy and also analyzing the cost effectiveness.

The rest of this paper contain Section 2 which explain the formula of load management strategy (LMS) and algorithm implementations, Section 3 presents the



case study and the results obtained including discussion on the analysis of the results data and its cost effectiveness and lastly Section 4 presents the conclusion of this study.

2. LMS FORMULATION

EToU tariff is in pricing unit. The simulation aims to optimize the use of electricity as well as to rearrange the load arrangement of manufacturing load profile. The reference equation have been referred in [1]. The general equation of optimum EToU electricity power is written in (1):

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

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

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

Where,

ΔP_{op} is the changes of off-peak desired load curve with the time change of $N=10$,

ΔP_{mp1} , ΔP_{mp2} , ΔP_{mp3} are the changes of mid-peak desired load curve with the time change of $N=2,3$ and 5 ,

ΔP_{p1} and ΔP_{p2} are the changes of peak desired load curve with time change of $N=1$ and 3 ,

TP_{op} is the EToU tariff rate for off-peak time zone,

TP_{mp} is the EToU tariff rate for mid-peak time zone,

TP_p is the EToU tariff rate for peak time zone.

The general equation for overall solutions of LSM strategies used in this study which is valley filling (VF), peak clipping (PC) and Load Shifting (LS) is written as in (3).

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

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

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

W_{VF} , W_{PC} and W_{LS} are the weightage or load apportioning of DSM strategies to be used in every load profile generated.

In achieving an efficient performance, there are several constraints of DSM strategies that must be set up which:

a) Valley Filling (VF) constraints

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

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

b) Peak Clipping (PC) constraints

$\Delta P_{ts,i}^{PC}$ is chosen during two biggest price of time segmentation loads and also the location of the maximum demand, where (ts) alteration follows

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

c) Load Shifting (LS) constraint

After VF and PC selection have been done, LS is the last one so that the rest of the segmentations will be performed by LS like proposed by [1]. The proposed LS procedure process is presented in (7), (8) and (9) accordingly.

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

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

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

Where,

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

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

ω is the weightage of load randomly decreasing and increasing at lower and upper bound load setting sets in (4).

d) Optimal Maximum Demand (MD) selection constraint

Maximum Demand plays crucial part in reducing cost based on EToU tariff. Suitable selection and allocation of MD at specific time zone are required. The MD selection respective to charge of MD is summarize in (10) and (11) meanwhile, the optimum MD charge obtained through selection of the combination both mid-peak and peak is shown in (12).

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

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



$$MD_P^{cost} \geq MD_{Optimum}^{cost} = MD_{MP}^{cost} \tag{12}$$

Where,

MD_{MP}^{cost} is the ideal power load determination at mid-peak area,

MD_P^{cost} is the ideal power load determination at peak area,

L_{TN} is the determined power load for number, n at specific time segmentation (ts),

MD_{MP}^{TP} and MD_P^{TP} are the charge of MD during mid-peak and peak.

e) Total energy constraint

Total energy before and after the optimization in addition of DSM strategies shall not exceed $\pm 5\%$ as referred in [10]. Equation (13) is the total energy consumption (kWh) constraint for EToU six time segmentation before and after optimization.

$$\sum E_T \cong \sum E'_T \tag{13}$$

Load Factor Index (LFI) written in (14) is used as verification for load profile improvement that are based on previous optimum formulation and constraints

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

Where,

$MD_{Optimum}^{kW}$ is the MD optimum selection in kW at peak or mid-peak zones,

$\sum E_{Tsn}$ is the total electricity consumption in kW for total n time segmentations,

t is the time of electricity usage.

3. ALGORITHM IMPLEMENTATION

In the ACO algorithm, there are two processes involved which are generating the ants process and updating the pheromones process. In the first process, a new set of ants will be generated in each iteration respective to the desired nodes. The probability of an ant to select a specific node as expressed in equation (17).

$$p(\alpha_{ij}|S_p) = \frac{r_{ij}^\alpha \times \eta_{ij}^\beta}{\sum r_{ij}^\alpha \times \eta_{ij}^\beta} \tag{17}$$

Where,

$p(\alpha_{ij}|S_p)$ is probability that the limit α_{ij} will be selected in line with the partial solution S_p ,

α_{ij} is node i to node j limit,

r_{ij} is the α_{ij} pheromone values,

η_{ij} is a heuristic value, or the inverse of the cost after going through limit α_{ij} ,

α is the importance factor of pheromone,

β is the importance factor of heuristic.

After the trails have been updated after the ants have completed their solution, updating pheromone process will start. Equation (18) and (19) presents the process of updating the pheromone evaporation and reinforcement accordingly.

$$r_{ij} = (1 - \rho) \times r_{ij} \tag{18}$$

Where,

r_{ij} is the value of pheromone at the limit ranging from i to j ,

ρ is the pheromone evaporation factor

$$r_{ij} = r_{ij} + \sum \Delta r_{ij} \tag{19}$$

Where $\sum \Delta r_{ij}$ is the pheromone that will be added by an ant to the trail, that rely on the length of the trail that used by the ants.

The four steps of ACO algorithm that has been applied to this study are:

Step 1: Ants are initialized by setting $\alpha = 1, \beta = 0$ and $\rho = 0.3$ referred to [11], [12] and [13]. The ants expressing a possible initial load profile set to identify the change in each electricity cost or in the algorithm is called nodes in 24-hour time. In the next step, the fitness value obtained is used.

Step 2: The constraints are formulated and the cost is identified. The pheromone values that have been updated will be engaged in the EToU formulation in form of MD cost and the DSM strategy as in (2) until (12) accordingly. The best cost value in first process is chosen from the latest update of total electricity cost in six-time segmentation. The second process of finding the updated ants pheromones will start after the first process in ACO is done.

Step 3: The best cost value obtained during the process of updating the pheromones are used to determine the best total energy cost covering all segmentations, while the ideal load profile represent by the best ants is developed. Once again, (18) and (19) are applied in this step.

Step 4: After the requirements for the best cost has been achieved, in order to satisfy the constraints, the achieved value of cost is concluded to be convergence value. If the requirement is not yet fulfilled, the process will begin all over again to find the new possible ideal setting of ants list. In this step, the contribution of electricity energy cost and MD cost to the contribution of LFI is generated.

4. RESULTS AND DISCUSSION

In proving that the proposed method is effective, tests have been conducted by using a load profile of a manufacturing that produce medicine. A one-week load profiles from three same type of same manufacturing production are compressed into one day average load



profile that contain 24 hours' time. A one-week load profile of the data taken is satisfy to follow the audit standard that has been set by Energy Commission of Malaysia [14].

4.1 Case Study

The arrangement of the case study by weightage that have been set for this project is as follow:

- Case 1:** Baseline of the flat ToU tariff rate.
- Case 2:** E1 EToU tariff rate without DSM strategies and without ACO algorithm.
- Case 3:** E1 EToU tariff rate without DSM strategies and using ACO algorithm.
- Case 4:** E1 EToU tariff rate by using 10% of the DSM strategies and ACO algorithm.
- Case 5:** E1 EToU tariff rate by using 20% of the DSM strategies and ACO algorithm.
- Case 6:** E1 EToU tariff rate by using 30% of the DSM strategies and ACO algorithm.

The adjustment of load management strategies has been set to 10%, 20% and 30% as the limitation for this study. The weightage for the LM is expected to be maximum of 30% due to the limitation of the manufacturing to adjust more load in involving in the ETOU program The analysis of these six cases will be discussed in the next section.

4.2 Analysis of Results Data

The output simulation of energy power consumption for all six cases using ACO algorithm are shown in Figure-1. From the figure, it can be observed that after the implementation of DSM strategies and ACO algorithm, the power consumption based on 24 hours operation was decreasing. It is also can be observed that the power consumptions in off peak that is from 12:00 a.m until 7:00 a.m are increasing that lead to the decreasing of power consumption during peak hours which at 11:00 a.m. to have more closer look on the power consumption changed, case 6 and case 2 has been compared. Figure-2 shows the comparison of electricity power consumption of normal EToU with EToU that have been implemented with 30% load adjustment and ACO algorithm. From the figure, the power consumption of case 6 can be seen increasing from 22:00 p.m until 7:00 a.m (off-peak zones). The increase is due to the impact of load shifting. And then it can be observed that the power consumptions are slightly decreasing from 14:00 p.m until 16:00 p.m (peak zones). From there, it can be observed that the load-shifting and peak clipping strategies have successfully decrease the electricity power consumption during the peak time. The highest power consumption has been recorded at 13:00 p.m (mid-peak zone) indicating that the demand has been successfully shifted from peak to mid-peak. This shows that DSM strategies applied are efficient and industrial customers can surely manage their load using this load weightage adjustment method.

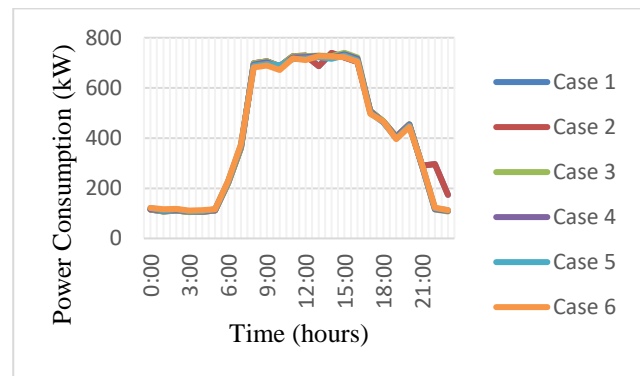


Figure-1. Power Consumptions of all six cases.

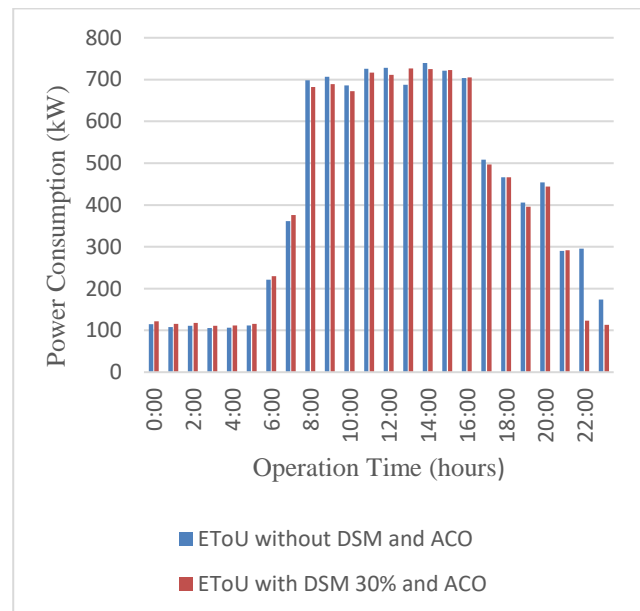


Figure-2. Comparison of EToU electricity power

4.3 Analysis of Cost-Effectiveness

Table-1 presents the total output of the simulation results of Matlab software. The results chosen are the best cost obtained after recording 10 times of different simulation results. The iteration of ACO algorithm is set to 100. Referring to Table-1, the baseline cases that have been calculated manually which is case 1 and case 2 have different consumption cost. The minimum cost was recorded in case 1 which is by using flat ToU tariff rate pricing. For case 3, the consumption cost is slightly reduced by using optimization algorithm of ACO although with 0% weight adjustment. This is due to ACO algorithm working principle which is finding the best minimum cost. Regarding the load adjustment of DSM strategies, the decreasing consumption cost can be observed in case 4 until case 6. In case 6 with the load adjustment of 30%, the price has decreasing 15% from the normal EToU price. The maximum demand also has been shifted from peak of case 2 to mid-peak of case 6 which achieves the DSM strategies aim to decrease the consumption of energy during peak hour. The load adjustments with the help of ACO algorithm has successfully minimize the power



consumption and price of the three cases when compared to the baseline cases.

It is also noticed that to reduce the cost of electricity consumption, the maximum demand needs to be in mid-peak zone. Only then the cost will be reducing

significantly. The reduction of maximum demand cost is contributing to the LFI improvement. Between case 3 to case 4, the maximum LFI value are obtained from case 3. Indeed, better LFI indicates that the DSM strategies implemented are working.

Table-1. Summary of the results for energy consumption, maximum demand, total electricity cost and LFI.

Cases	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Energy Consumption (kWh)	10231	10231	10043	10021	9998	9983
MD (kW)	740	740	740	734	729	727
MD Location	Peak	Peak	Peak	Peak	Peak	Mid-Peak
Energy Consumption Cost (RM)	3448	3895.665	3865.26	3850.125	3834.64	3827.053
MD Cost (RM)	21904	26270	26270	26057	25879.5	21519.2
Total Electricity Cost/day	25352	30165.66	30135.26	29907.13	29714.14	25346.25
LFI	0.5761	0.5761	0.5655	0.5689	0.5714	0.5722

5. CONCLUSIONS

The optimization method by using algorithm along with the implementation of DSM strategy that has been used in this study has been proven to be able to reduce the cost of industrial E1 EToU pricing. The load weightage apportioning of load management strategy in this study has manage to minimize the electricity usage of a manufacturing load profile. The performance of optimization algorithm, ACO has been analyzed and its ability to handle energy load profile are making it easier for optimization process. In conclusion, the objective has been achieved in this study.

ACKNOWLEDGEMENT

The authors would like to thank Universiti Teknikal Malaysia Melaka (UTeM) for the support given.

REFERENCES

- [1] M. Sulaima, N. Dahlan, and Z. Yasin. 2019. Effective Electricity Cost Management in a Manufacturing Operation by Using Optimal ETOU Tariff Formulation. *Int. J. Electr. Electron. Syst. Res.* 15: 82-93.
- [2] Y. Wang and L. Li. 2014. *Int. J. Production Economics* Time-of-use based electricity cost of manufacturing systems : Modeling and monotonicity analysis. *Intern. J. Prod. Econ.* 156: 246-259, doi: 10.1016/j.ijpe.2014.06.015.
- [3] S. Tenaga. 2016. Laporan Suruhan Jaya Tenaga. 2554, [Online]. Available: <http://library1.nida.ac.th/termpaper6/sd/2554/19755.pdf>.
- [4] R. Li, Z. Wang, C. Gu, F. Li and H. Wu. 2016. A novel time-of-use tariff design based on Gaussian Mixture Model. *Appl. Energy*, 162: 1530-1536, doi: 10.1016/j.apenergy.2015.02.063.
- [5] A. Hatami, H. Seifi and M. K. Sheikh-El-Eslami. 2011. A stochastic-based decision-making framework for an electricity retailer: Time-of-use pricing and electricity portfolio optimization. *IEEE Trans. Power Syst.* 26(4): 1808-1816, doi: 10.1109/TPWRS.2010.2095431.
- [6] N. A. M. Azman, M. P. Abdullah, M. Y. Hassan, D. M. Said and F. Hussin. 2017. Enhanced time of use electricity pricing for industrial customers in Malaysia. *Indones. J. Electr. Eng. Comput. Sci.* 6(1): 155-160, doi: 10.11591/ijeecs.v6.i1.pp155-160.
- [7] M. F. Sulaima, N. Y. Dahlan, M. H. Isa, M. N. Othman, Z. M. Yasin and H. A. Kasdirin. 2019. ETOU electricity tariff for manufacturing load shifting strategy using ACO algorithm. *Bull. Electr. Eng. Informatics.* 8(1): 21-29, doi: 10.11591/eei.v8i1.1438.
- [8] B. N. Silva and K. Han. 2019. Mutation operator integrated ant colony optimization based domestic appliance scheduling for lucrative demand side management. *Futur. Gener. Comput. Syst.* 100: 557-568, doi: 10.1016/j.future.2019.05.052.
- [9] M. Marzband, E. Yousefnejad, A. Sumper and J. L. Domínguez-García. 2016. Real time experimental implementation of optimum energy management



system in standalone Microgrid by using multi-layer ant colony optimization. *Int. J. Electr. Power Energy Syst.* 75: 265-274, doi: 10.1016/j.ijepes.2015.09.010.

- [10] M. F. Sulaima, N. Y. Dahlan, Z. M. Yasin, N. A. M. Asari and Z. H. Bohari. 2017. 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.*, doi: 10.11591/ijeecs.v8.i1. pp. 253-261.
- [11] P. Siano. 2014. Demand response and smart grids - A survey. *Renew. Sustain. Energy Rev.*, 30: 461-478, doi: 10.1016/j.rser.2013.10.022.
- [12] Y. Chai, Y. Xiang, J. Liu, C. Gu, W. Zhang and W. Xu. 2019. Incentive-based demand response model for maximizing benefits of electricity retailers. *J. Mod. Power Syst. Clean Energy*, 7(6): 1644-1650, doi: 10.1007/s40565-019-0504-y.
- [13] N. S. M. Nazar, M. P. Abdullah, M. Y. Hassan and F. Hussin. 2012. Time-based electricity pricing for Demand Response implementation in monopolized electricity market. doi: 10.1109/SCORED.2012.6518634.
- [14] 2016. Suruhanjaya Tenaga (Energy Commission), *Electrical Energy Audit Guidelines*.