Particle Swarm Optimization for Aggregators in Smart Grids Demand Response Program

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Abstract. Demand Response (DR) is changes in electricity usage by end-customers from their normal consumption patterns in response to incentive payment designed to convince lower electricity usage particularly in peak periods. Typically, there are three main players in the DR system; an electric utility operator, a set of aggregators, and end-customers. This study presents the model where a set of competing aggregators act as mediators between the utility operator and end-customers. The operator aims to minimize its operational cost and offers rewards to aggregators. Profit-maximizing aggregators compete to sell DR services to the operator and provide compensation to end-customers to modify their desirable consumption pattern. Finally, end-customers seek to compromise between compensation from the aggregator and having to adjust their electricity usage pattern. The objective of the model is to determine the best set of incentives for various time periods to the end-customers in order to satisfy all stakeholders. The DR program is a challenging optimization problem especially when the problem-size is very large. Therefore, this paper presents an application of Particle Swarm Optimization (PSO) in smart electricity grid demand response system. The experimental results show that PSO can be efficiently applied to the problem and provide good solutions.

Keywords: load aggregators, smart grids, demand response, particle swarm optimization

1. INTRODUCTION

Demand response (DR) is a change in the power consumption profile of an electricity utility customer to better match the power supply of the utility operator. Since there are limits to what can be achieved on the supply side, some generating units can take a long time to come up to full power, and some units may be very expensive to operate. In addition, demand can be sometimes greater than the capacity of all available power plants. Therefore, DR seeks to adjust the customer demand instead of increasing the power supply capacity. In DR program, the incentive payment program is used to convince customers to adjust their power consumption profile. Particularly, it is expected that customers shift their demand in peak periods to other time periods in order to reduce the overall power generation cost.

Typically, there are three main players in the DR system; an electric utility operator, a set of aggregators, and end-customers. Aggregators are new potential players in the electricity market that act as mediators between the utility operator and end-users. Since the aggregator is responsible for a large amount of total demand in the DR market, it can negotiate on behalf of end-users with the operator more efficiently. Nowadays, the current role of aggregators includes paying a monthly fee to the controlled users in order to gain direct control of their electricity usages (Gkatzikis et al., 2013).

In Thailand, the electricity generating authority has recently initiated Thailand Demand Response Preliminary Project with the purpose to reduce the amount of power consumption in some time-periods during the summer. However, the load aggregators were not yet considered to be included in the DR system. Pasom et al. (2015) studied the potential of demand response measures of the commercial building in Thailand based on the actual test from three existing buildings in Bangkok. The results showed that some significant power usages can be reduced; however, the reduced demand also depended on the level of benefit offered to the building.

There are few studies have been done on the role of aggregator in the smart grids DR program. Papavasiliou et al. (2010) presented a settlement mechanism using supply function bidding for optimizing real time electricity consumption schedule in an automated demand response control system. Kim and Thottan (2011) proposed a market model where microgrids sell their surplus power to a utility via aggregators. Thus, aggregators collect power from microgrids and resell it to the utility. Based on this two-stage stackelberg game, efficient market equilibrium was achieved using the tatonnement process and supply function bidding. Gkatzikis et al. (2013) proposed a hierarchical market for the smart grid where a set of competing aggregators act as intermediaries between the utility operator and the end-users. The mathematical model was also presents to optimize each of player objective.

The DR program is a challenging optimization problem especially when the problem-size is very large. The number end-customers can be up to 10,000 companies, and using exact solution methods would be highly time-consuming. Therefore, metaheuristic approaches maybe more preferable to deal with this problem.

This study presents the first application of Particle Swarm Optimization (PSO) in a smart electricity grid demand response system. The objective is to determine the best set of incentives for various time periods to the end-customers in order to satisfy all stakeholders. The remainders of the paper are organized as follows. Section 2 presents a problem description. Section 3 describes the original PSO framework, and an application of the PSO to the demand response program is presented in Section 4. The numerical experiments are reported in section 5. Finally, conclusion is provided in Section 6.

2. PROBLEM DESCRIPTION

This study is motivated by the problem formulation of demand response market (Gkatzikis et al., 2013). In their model, an electricity market consisted of three players; one utility operator, a set of aggregators $A = \{1, 2,\dots, J\}$, and a set of end-users. It was assumed that each customer is assigned to a pre-determined aggregator, and the customers do not move between aggregators. The problem focused on the day-ahead market and assumes that times in one day were divided into T equal periods ($T = \{1, 2,\dots, T\}$). The demand response market was formulated according to the following optimization problems.

2.1 The Role of Utility Operator

In the utility operator's point of view, in order to meet the total customer demand, the operator has a choice of either activating costly power plant or purchasing electricity from third parties. Normally, the cost of generating electricity ($c = c(t)$) is vary with time due to availability of supply. In a day-ahead market, the total customer demand is accumulated as W Watts ($\sum_{t\in T} y_t = W$). It is assumed that a customer is charged by the flat pricing policy of fixed price, q_f, per Watt. Therefore, on a daily basis, an operator receives the total income of $q_f W$ from customer payment.

In DR market, it is desirable that the electricity consumption pattern of customers will be distributed more evenly during the timespan; however the total demand during a day remain the same. Since the operator income is fixed, the problem of an operator becomes to seek for cost minimization. An operator provides rewards $\lambda = \{\lambda_j \geq 0 : j \in A\}$ to the aggregators so that they perform DR on their behalf. Particularly, the operator is willing to provide a portion $\hat{\lambda} = \sum_{j\in A} \lambda j$ of its DR gain to the aggregators. The DR gain ($\Delta c(y(\lambda))$ is the reduction of the power generation cost that results from reward λ and is given by equation (1).

$$\Delta c\big(y(\lambda)\big) = \sum\nolimits_{t\in T} \Delta c_t(y_t(\lambda)) \;\; = \sum\nolimits_{t\in T} [c_t^0 - c_t(y_t(\lambda)] \qquad (1)$$

Where c_t^0 is the power generation cost at timeslot t if no DR is applied.

Therefore, the problem of an operator is formulated as the following model in equation (2)-(4) to minimize its operational cost.

$$\min_{\lambda} \sum_{t\in T} c_t(y_t(\lambda)) + \hat{\lambda}\Delta c_t(y_t(\lambda)) \qquad (2)$$

$$s.t. \quad 0 \leq \hat{\lambda} \leq 1 \qquad (3)$$

$$\lambda_j \geq 0 \qquad , \quad \forall j \in A \qquad (4)$$

The objective function of the operator is to minimize both power generation cost and its reward to the aggregators for their services. In real-application, it is noted that the reward provided to the aggregators depends only on the quality of their aggregate DR services.

2.2 The Role of Aggregators

Provided that each customer is assigned to an aggregator by a contract, D_j is denoted as the total demand of all users under aggregator j. In the demand response market, the aggregators need to provide DR services to the operator and guarantee that the end-users reduced their electricity bills.

In particular, each aggregator aims to smooth the electricity consumption pattern of its users and receive compensation for the cost savings for the operator due to the changed consumption pattern. It is assumed that an aggregator motivates users to modify their power consumption pattern through dynamic compensation per unit of power. Thus, an aggregator j provides the compensation vector $p_j = \{ p_j : t \in T\}$. Let $d_j = \{ d_{jt} : t \in T\}$ denote the cumulative load of aggregator j at time slot t, over all demands in D_j, that results from compensation p_j.

The DR gain (Δc) of an aggregator j does not only depend on its own compensation strategy p_j, but also the compensation strategy of other aggregators which are denoted by $P_{-j} = (p_1,\dots p_{j-1}, p_{j+1,\dots,} p_J)$. The objective of aggregator j is to maximize its net profit by solving the following optimization problem in equation (5) and (6):

$$\underset{p_j}{\text{Max}}\ \lambda_j \Delta c(\mathrm{p}_j, \mathrm{P}_{-j}) - \sum_{t\in T} p_{jt} d_{jt}(p_j) \tag{5}$$

$$s.t. \qquad p_{jt} \geq 0 \quad , \quad \forall t \in T \tag{6}$$

2.3 The Role of End-Customers

When no DR is applied, the end-user i is assumed to have electricity consumption pattern as $x_i^0 = \{x_{it}^0 : t \in T\}$. In each day, there are peak periods in which the electricity usages are in high level. The aggregators then provide monetary compensation in order to motivate users to modify their usage patterns to be smoother with the assumption that the total demand W_i is fixed and independent of the provided compensation. Thus, a user i has a fixed daily cost of $q_f W$.

When DR is applied, the end-user i modifies its usage pattern from x_i^0 to x_i ($x_i = x_{it} : t \in T$). Even though a user receives monetary compensation, adjusting usage behavior causes some dissatisfaction. In the model, the disutility function V_{it} $\{V_{it}(x_{it}) = v_i(x_{it} - x_i^0)^2\}$ is introduced where inelasticity parameter v_i of demand i indicates different behaviors of diverse users. Small values of v_i imply the minimal dissatisfaction if their consumption pattern is modified. On the other hand, large values of v_i denote more dissatisfaction of demand modification.

According to above conditions, the objective of a user is to maximize its net payoff which is determined by the compensation received from the aggregator minus the dissatisfaction as shown in the follow model (equation (7) - (9)).

$$\max_{x_i} \sum_{t\in T} [x_{it} p_{jt} - V_{it}(x_{it})] \tag{7}$$

$$s.t. \qquad x_{it} \geq 0 \quad , \quad \forall t \in T \tag{8}$$

$$\textstyle\sum_{t\in T} x_{it} = W_i \tag{9}$$

In this study, the benchmark scenario of full information (Gkatzikis et al., 2013) is adopted. In this scenario, the utility operator has global knowledge of all system parameters which include electricity consumption pattern x_i, the inelasticity parameters v_i and the set of allocated users to each aggregator j. This scenario provides insights on how misaligned are the interests of the market entities and whether disclosing this information to the operator is beneficial for the lower levels. It also serves as a benchmark regarding the cost of the operator (Gkatzikis et al., 2013).

Therefore, the problem is formulated as a multilevel optimization problem, and three decision levels need to be made:

1) The operator computes the reward for aggregator λ_j to minimize its operational cost.
2) The aggregators determine their compensation strategy to end-users to maximize their net profit.
3) The users modify their demand pattern according to the compensation provided by the aggregators to maximize their net payoff.

The decision in level 2 and 3 can be merged into one optimization problem in order for an aggregator j to determine the compensation p_j to achieve maximum net profit. The merged model is shown in equation (10) and (11).

$$\max_{\boldsymbol{p}_j} \left\{ \lambda_j \sum_{t=1}^{T} \Delta c_t \left(\sum_{i\in D_j} x_{it}(\boldsymbol{p}_j), \boldsymbol{P}_{-j} \right) - \sum_{t=1}^{T} p_{jt} \sum_{i\in D_j} x_{it}(\boldsymbol{p}_j) \right\} \tag{10}$$

$$p_{jt} \geq 0, x_{it} \geq 0, \quad \forall i \in D_j, t \in T_j \tag{11}$$

For the decision in level 1, the operator has to find the monetary reward vector λ* that minimizes its operational cost. However, the exact impact of its rewards on demand distribution is difficult to quantify, since it also involves the optimization problems of the lower two levels. In particular, the operator needs to know the analytical expression of $d_{jt}(p_j(\lambda_j))$. This problem falls within the class of multi-level optimization problems, which are particularly difficult to solve. Therefore, in order to characterize the DR solution from the operator's point of view, the reward strategy of the operator can be calculated numerically.

3. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a population based random search method that imitates the physical movements of the individuals in the swarm as a searching mechanism. The original PSO algorithm was proposed by Kennedy and Eberhart in 1995. Its concept was originated from the behavior of fish schooling or birds flocking. In PSO, a solution is represented as a particle, and the population of solutions is called a swarm of particles. Each particle has two main attributes: position and velocity. The key concept of PSO is that each particle learns from the cognitive knowledge of its experiences and the social knowledge of the swarm to guide the particle to the better position. A particle moves to a new position using the updated velocity. Once a new position is reached, the best position of each particle and the best position of the swarm are updated as needed. The velocity of each particle is then adjusted based on the experiences of the particle. These processes are repeated until a stopping criterion is met. The velocity and position in the original PSO are updated and formulated as equation (12) and (13).

$$\omega_{id}(t+1) = \omega_{id}(t) + c_p u\left(\psi_{id}^{p} - q_{id}(t)\right) + c_g u\left(\psi_{id}^{g} - q_{id}(t)\right) \quad (12)$$

$$q_{id}(t+1) = q_{id}(t) + \omega_{id}(t) \quad (13)$$

Where as

q_{id} : current position of d^{th} dimension of i^{th} particle

ω_{id} : velocity of d^{th} dimension of i^{th} particle

ψ_{id}^{p} : personal best position of d^{th} dimension of i^{th} particle

ψ_{id}^{g} : global best position of d^{th} dimension of i^{th} particle

c_p : weight of personal best position term

c_g : weight of global best position term

u : uniform random number in range [0,1]

Due to its ease of implementation and computational efficiency, PSO has been successfully applied and shown its effectiveness in many application areas, not only for continuous problem domains (Zhang et al., 2007; Sun and Gao, 2008; Goh et al., 2010) but also combinatorial optimization problems such as scheduling (Chandrasekaran et al., 2007; Liu et al., 2007; Zhixiong and Shaomei, 2012) and forecasting (AlRashidi and El-Hawary, 2006, 2007).

4. APPLICATION OF PSO TO DEMAND RESPONSE PROGRAM

This study presents how PSO can be employed to deal with demand response system. First, a solution of the problem is represented using particle dimensions in which its dimensions are set to be equal to the total number of compensation timeslots for all load aggregators. Consider an example of two aggregators who provide different incentives to the end-users for four periods of time during one day. Thus, the number of dimensions is equal to 8. Figure 1 illustrates solution representation encoding scheme where each value in a particle dimension is initially generated with a uniform random number in the compensation range.

	Aggregator 1				Aggregator 2			
Dimension d	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	5.23	1.97	4.34	2.46	6.71	5.58	6.47	2.87

Figure 1: Solution representation encoding scheme

Since there are two load aggregators in this example, in order to transform these numbers into a solution, the first four dimensions are assigned to Aggregator 1, and the next four dimensions are assigned to Aggregator 2. Then, for Aggregator 1, the number in the first dimension becomes the compensation of timeslot 1, and the number in the second dimension becomes the compensation of timeslot 2, and so on until the last compensation is determined. These processes are repeated for Aggregator 2. Finally, as shown in Figure 2, the compensation for all timeslots is derived, and the objective function can be evaluated.

	Aggregator 1				Aggregator 2			
Dimension d	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	5.23	1.97	4.34	2.46	6.71	5.58	6.47	2.87
Time Period	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
Compensation	5.23	1.97	4.34	2.46	6.71	5.58	6.47	2.87

Figure 2: Solution transformation

5. NUMERICAL EXPERIMENT

In order to evaluate the performances of PSO to the DR program, a dataset based on a realistic base-line electricity consumption pattern in some region in Thailand is generated. The dataset includes the daily electricity usage of diverse customers. Based on the model proposed by Gkatzikis et al. (2013), the disutility function is adopted with an inelasticity parameter v_i which is uniformly distributed in a range $[0, v_{max}]$. It is noted that $v = v_{max}/2$ is an average inelasticity value.

This study considers a market of a single utility operator, 3 aggregators, and 30 end-customers equally allocated among the aggregators. According to the model of Gkatzikis et al. (2013), the power generation cost function, $c(y_t) = r_t y_t$, is used, with the corresponding total demand y_t at each timeslot t. It is noted that r_t is the power generation cost per unit at each timeslot t. Figure 3 illustrates the summation of total demand and consumption pattern across a day where no compensation is provided to the users. Figure 4 shows the power generation cost of an operator associated with the total demand.

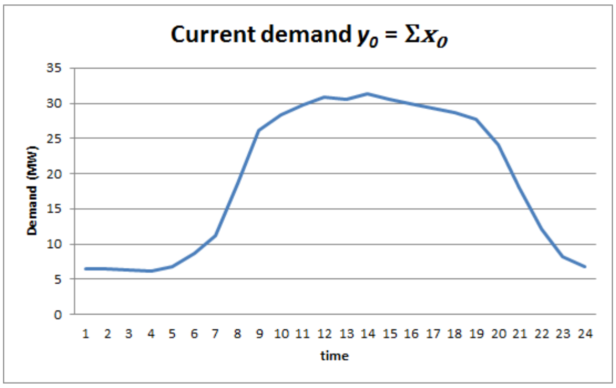

Figure 3: The total demand before applying DR.

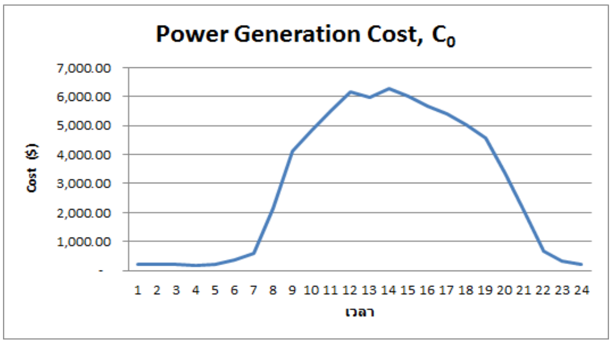

Figure 4: The operator's power generation cost before applying DR.

After DR is applied, it is expected some changes in the system. Figure 5 illustrates an average best set of incentives for various time periods to the end-customers in the case when $\hat{\lambda} = 0.9$ and inelasticity is low. It can be seen that the compensations for electricity consumption of the non-peak periods are higher than other periods, so it is expected that users modify their behavior. Figure 6 and 7 show the effects of DR program on the total demand and total operation cost, respectively. It is clearly seen that after DR program is applied, the total demand is more evenly distributed across a day which allows the consumption pattern smoother. In addition, the results show that, in the case of low values of inelasticity, the consumption is more evenly distributed compared to the case of the high value of user inelasticity due to the fact that the users are more willing to change their electricity consumption pattern in the case of low inelasticity. Therefore, inelasticity of demands, explained by inelasticity parameter v_i, plays a vital role on the final consumption load pattern.

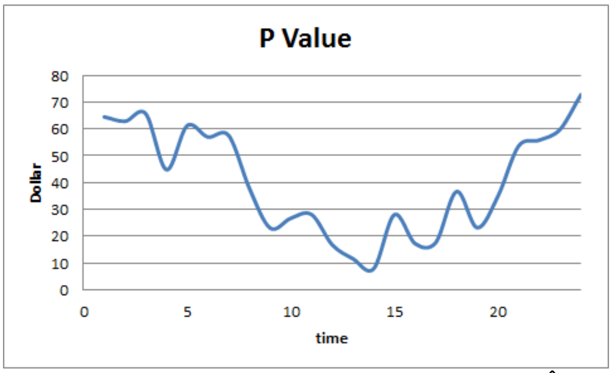

Figure 5: The average best set of incentives when $\hat{\lambda} = 0.9$

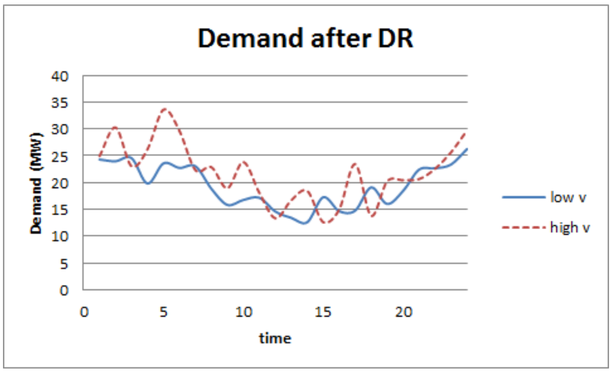

Figure 6: Electricity demand after applying DR.

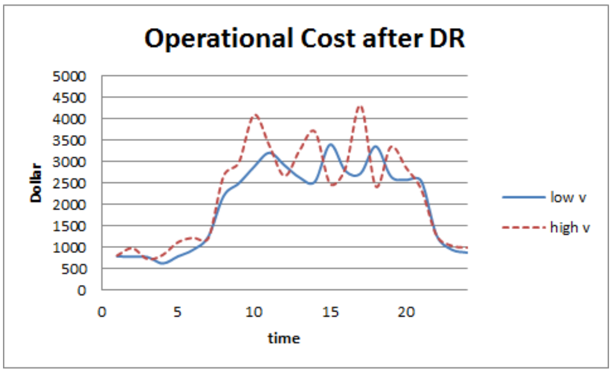

Figure 7: Operational cost after applying DR.

Next, the effects of different values of monetary reward to aggregator $\hat{\lambda}$ and inelasticity parameter v_i, on the benefit of all participating entities are evaluated. Figures 8-10 show the impact of DR program on the total cost of the operator, the net benefit of the aggregators, and the net payoff attained by the end-users respectively.

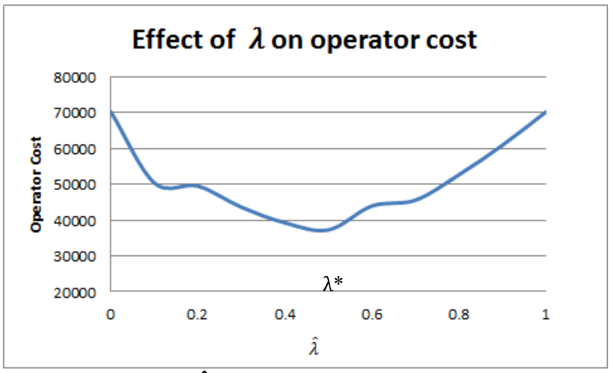

Figure 8: Effect of $\hat{\lambda}$ on operator cost

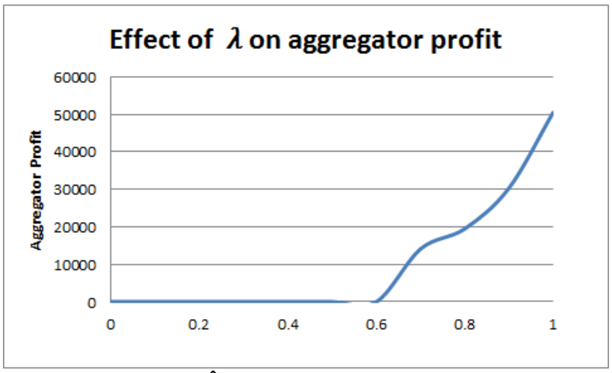

Figure 9: Effect of $\hat{\lambda}$ on aggregator Profit

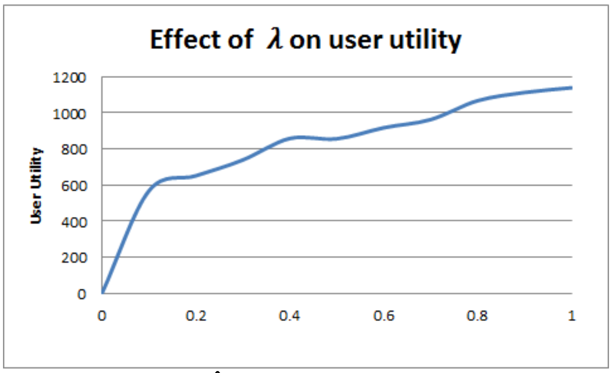

Figure 10: Effect of $\hat{\lambda}$ on user utility

According to Figure 8, an operator's minimum cost λ* is derived. It is observed that when the value of $\hat{\lambda}$ increases, the operational cost decreases; however, at the specific $\hat{\lambda}$, the operational cost begins to increase. Thus, an operator needs to carefully design how the reward should be provided to aggregators. In Figures 9 and 10, the net profit of aggregators and the net payoff of the end-users is an increasing function of $\hat{\lambda}$. It is easy to see that the aggregators only receive profit after some specific $\hat{\lambda}$ ($\hat{\lambda}$ = 0.6). Therefore, in this analysis, all participants can see how the design of rewards affects the whole system.

6. CONCLUSION

This study presents an implementation of Particle Swarm Optimization (PSO) for load aggregators in smart electricity grid demand response system. The model of demand response system is based on the hierarchical market structure with full information proposed in the literature. Due to its ease of implementation and computational efficiency, it is shown that PSO can be used as an alternative efficient solution method to provide good solution. However, in practical, the full information may not be necessarily available to an operator. In such case, each participant must carefully design the best-suit strategic plan for their own benefit.

The future research includes extending the problem with more practical constraints or improving the algorithm performances by incorporating some strategies to better balance exploration and exploitation ability of the search.

REFERENCES

AlRashidi, M. R. and El-Hawary, M. E. (2006) Emission economic dispatch using a novel constraint handling particle swarm optimization strategy. *Proceeding of 2006 Canadian Conference on Electrical and Computer Engineering*, 664-669.

AlRashidi, M. R. and El-Hawary, M. E. (2007) Hybrid particle swarm optimization approach for solving the discrete OPF problem considering the valve loading effects. *IEEE Transactions on Power Systems*, **22**, 2030-2038.

Chandrasekaran, S., Ponnambalam, S. G., Suresh, R. K. and Vijayakumar, N. (2007) Multi-objective particle swarm optimization algorithm for scheduling in flowshops to minimize makespan, total flowtime and completion time variance. *IEEE Congress on in Evolutionary Computation*, 4012-4018.

Gkatzikis, L., Koutsopoulos, I., and Salonidis, T. (2013) The role of aggregators in smart grid demand response markets. *IEEE Journal on Selected Areas in Communications*, **31**, 1247-1257.

Goh, C. K., Tan, C. K., Liu, D. S. and Chiam, S. C. (2010) A competitive and cooperative co-evolutionary approach to multi-objective particle swarm optimization algorithm design. *European Journal of Operational Research*, **202**, 42-54.

Kennedy, J. and Eberhart, R. (1995) Particle swarm optimization. *Proceedings of the IEEE International Conference on Neural Networks, NJ*, 1942-1948.

Kim, H. and Thottan, M. (2011) A two-stage market model for microgrid power transactions via aggregators. *Bell Labs Technical Journal*, **16**, 101-107.

Liu, B., Wang, L. and Jin, Y. H. (2007) An Effective PSO-Based Memetic Algorithm for Flow Shop Scheduling. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, **37**, 18-27.

Papavasiliou, A., Hindi, H. and Greene, D. (2010) Market-based control mechanisms for electric power demand response. *Proceeding of IEEE Conference on Decision and Control, GA,*1891-1898.

Pason, W., Therdyothin, A., Nathakaranakule, A., Prapanavarat, C. and Limmeechokchai, B. (2015) The potential of demand response measures of commercial buildings in thailand. *Energy Procedia: 2015 International Conference on Alternative Energy in Developing Countries and Emerging Economies*, **79**, 1015-1020.

Sun, L. Q. and Gao, X. Y. (2008) Improved chaos-particle swarm optimization algorithm for geometric constraint solving. *Proceeding of international Conference on Computer Science and Software Engineering*, **2**, 992-995.

Zhang, J., Huang, D. S,, and Liu, K. H. (2007) Multi-sub-swarm particle swarm optimization algorithm for multimodal function optimization. *IEEE Congress on Evolutionary Computation*, 3215-3220.

Zhixiong, L. and Shaomei, W. (2012) A Hybrid particle swarm optimization algorithm for the permutation flowshop scheduling problem. *Optimization Theory, Decision Making, and Operations Research Applications of the series Springer Proceedings in Mathematics & Statistics*, **31**, 91-101.