http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (10): 1895-1904, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.1895.1904

Efficient Scheduling of Electricity Consumption for Smart Grid with Uncertainty in Renewable Supply

Xiaojie Sun, Yuan Wu, Xiao Liang, Yi Yang and Limin Meng
College of Information Engineering, Zhejiang University of Technology, Hangzhou, 310023, China

Abstract: Future smart grid has been conceived to be able to improve efficiency and stability of the grid operations. Based on the smart meter and advanced mechanism of two-way communications, Energy-Users (EUs) are able to receive real-time signalling (e.g., the electricity price) from the grid and schedule their energy consumption to optimize their objectives of interest correspondingly. Besides the conventional fuel-based energy supply, renewable energy supplies, e.g., solar and wind power, are expected to play important roles in smart grid. Despite their advantages in lowering the electricity-provisioning cost and being environment-friendly, renewable supplies usually suffer from uncontrollable and volatile generations, which result in great fluctuations in their provisioning. Therefore, it is indispensable for EUs equipped with renewable energy suppliers to take a careful tradeoff between exploiting the benefit from the renewable energy and controlling the adversary impact due to its volatility. Based on this motivation, this study aims at jointly optimizing the EU's average energy-acquisition cost as well as its fluctuation. This problem is formulated as a nonconvex optimization problem and this study proposes an efficient Layered Particle Swarm Optimization (L-PSO) algorithm to determine the EU's optimal scheduling of energy consumptions. Our numerical results show how EU can trade off between benefiting from the renewable supplies and suffering from the associated fluctuation through tuning the weighting-factors.

Key words: Smart grid, energy scheduling, renewable energy, nonconvex optimization problem

INTRODUCTION

Future smart grid, an advanced power grid system which integrates efficient information infrastructure, is expected to significantly improve stability and efficiency of the grid operations (Pothamsetty and Malik, 2009). Among those new features of smart grid, the efficient demand-response and great exploitation of renewable energy are believed to be of great importance to change the way in which Energy-Users (EUs) consume electricity (U.S. Department of Energy, 2009; Frye and Cisco Internet Business Solutions Group, 2008; Ghader *et al*., 2006). In smart grid, based on the two-way communication and smart meters, each EU can receive real-time signaling (e.g., the real-time electricity price) from grid and thus schedule its electricity consumption for different appliances to trade off between its performance of interests and the associated electricity-acquisition cost, thus facilitating the so-called efficient "demand-response". Besides acquiring the electricity from the grid, EUs in future smart grid are expected to be able to reap renewable energy, e.g., through the solar panel and wind turbine, forming the so-called distributed generation system. Exploiting of renewable energy gains the EUs great advantages in lowering its electricity-provisioning cost and being environment-friendly. However, the renewable sources usually suffer from uncontrollable volatility, which results in great fluctuation in energy-provisioning. This fluctuation in energy-provisioning from distributed renewable sources in fact implies that the EU will have an uncertainty in electricity-acquisition from the main grid as well as an uncertainty in its acquisition-cost consequently. Minimizing this acquisition-cost in long-term is one of the key interests from the EU's perspective. However, intuitively, minimizing this long-term acquisition-cost aggressively may incur a large fluctuation, which in fact adversely impairs the EU's experiences. Imagine that the EUs usually dislike greatly fluctuating and unpredictable monthly bill of their electricity consumptions. Thus, a good scheme for each EU to schedule its energy consumption is to take account of both the long-term average acquisition-cost as well as its fluctuation, and further to trade off between these two aspects according to the EU's preference. This motivates this study. Specifically, this study formulates an EU's energy scheduling problem which aims at jointly

Corresponding Author: Yuan Wu, College of Information Engineering, Zhejiang University of Technology, Hangzhou, 310023, China Tel: +8657185290372

optimizing the EU's average energy-acquisition cost and its fluctuation within a target period of interest.

The key contributions of this study can be summarized as follows:

- This study formulates a multi-objective optimization problem for the EU's energy scheduling which jointly takes account of the EU's average energy-acquisition cost and its fluctuation within a target period of interest. This study's results verify that the EU has a tradeoff between minimizing its average cost and controlling the corresponding fluctuation in acquisition, and can obtain its satisfactory operational point which trades off between these two aspects by tuning their corresponding weighting factors
- Despite the non-convexity of the formulated problem in general, this study identifies a separable structure of the problem and proposes a Layered Particle Swarm Optimization (L-PSO) algorithm to determine the EU's optimal energy scheduling. In comparison with the conventional PSO, this study's layered approach greatly reduces the number of decision variables and hence speeds up the randomized search via PSO to approach to the optimal solution

RELATED WORK

The mechanism of two-way communications between grid operations and energy-users is critical to enable the demand response of smart grid. Based on this two-way communications mechanism, Mohsenian-Rad *et al.* (2010) proposed autonomous and distributed demand-side energy management schemes. Samadi *et al.* (2010) proposed a Vickrey-Clarke-Groves mechanism to maximize the social welfare. However, these previous studies did not take account of the renewable energy in their demand response model. Future smart grid will be featured by its great exploitation of renewable energy, which helps reduce the marginal energy-provisioning cost and the emission of greenhouse gas. However, the generation of renewable energy from renewable sources (e.g., solar panel and wind turbine) is usually uncontrollable and volatile, which result in a great uncertainty in energy-provisioning when incorporating renewable energy. This uncertainty will impose instability and inefficiency to the grid operations. Existing studies proposed different schemes to predict the generation of renewable energy (Jiang and Low, 2011a, b). However, these schemes usually suffer from limited accuracy. Hence, the volatility of renewable energy provisioning needs to be carefully taken care of in demand response to ensure it's efficient and stable usage.

The efficient demand-response is also of great importance to change the way in which EUs consume electricity. Conejo *et al.* (2010) maximized the utility of the consumer while minimizing the load per hour. Their studies mostly focused on optimizing the average performance. Li *et al.* (2011) maximized each household's net-benefit while satisfying users' consumption and the system's physical constraints. Pedrasa *et al.* (2010) maximized the net-benefits of system by scheduling their distributed energy resources. Mohsenian-Rad and Leon-Garcia (2010) achieved a tradeoff between the electricity cost and the waiting time for each appliance's operation by using an optimal residential energy consumption scheduling method. Although the above schemes proposed by different studies perform well under different scenarios. However, because of the stochastic nature of renewable energy, EU's energy acquisition-cost is naturally random. In this case, this study proposes to jointly optimize the EU's average energy-acquisition cost as well as its fluctuation with guarantee of its consumption requirement.

SYSTEM MODEL AND PROBLEM FORMULATION

This study considers the model of a residential smart grid. Specifically, in this model, the grid and Energy-Users (EUs) are connected by both power lines and two-way communication network. Each EU is equipped with a smart meter to receive the electricity price and control its electricity scheduling for its group of appliances. The electricity-acquisition from the grid as well as its allocations to different appliances is all control-variables to be optimized in the following problem formulation. As stated earlier, in addition to the electricity acquisition from grid, each EU is able to reap renewable energy (e.g., through the solar panel and distributed wind turbine) as a supplementary electricity supply. In this model, this study considers a group of EUs denoted by $\mathcal{U} = \{1, 2,\ldots, U\}$. This model is shown in Fig. 1, in which "app" denotes EU's appliance.

Model of EU's energy consumption: Each EU is equipped with a smart meter, which is in charge of its electricity scheduling for different appliances. Specifically, this study uses $q^t_{u,a}$ to denote the scheduled electricity consumption for appliance a of EU u at slot t. Since this study focuses on the optimal energy scheduling for a single EU, this study does not explicitly include the subscript "u" in the rest of this study. Let $\mathcal{H} = \{1, 2, .., H\}$ denote the scheduling horizon of interest. This study

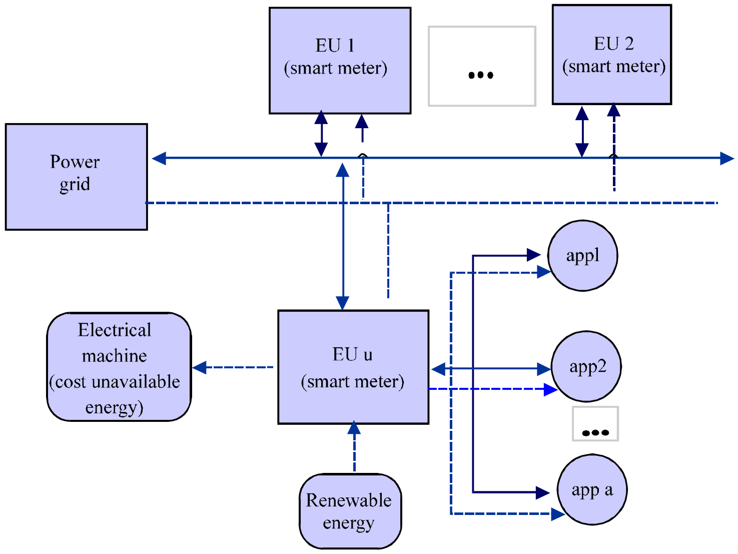

Fig. 1: The model of a residential smart grid

considers two representative types of appliances, i.e., appliances with fixed demands (denoted by Type-A) and appliances with shiftable demands (denoted by Type-B), respectively.

The Type-A appliances include all the background appliances, i.e., each Type-A appliance consumes a fixed amount of energy per unit time within its working period. Examples of Type-A appliances include lighting, refrigerator, computer, etc. Next, this study introduces the energy consumption constraints of Type-A appliances. As a background appliance, each $a \in A$ appliance works in a fixed working period $T_a \in \mathcal{H}$ during which it consumes r^t_a energy per time slot. Mathematically, it is given by:

$$q^t_a = \begin{cases} r^t_a, & t \in T_a, a \in A \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

For each Type-B appliance, its total energy consumption within a preferred time period should be greater than a fixed total energy. The electricity consumption of each Type-B appliance is shiftable in the sense that it can adjust its consumption of electricity at each slot within its working period. Examples include washer/dryer, dishwasher, plug-in hybrid electric vehicle, etc. For each appliance $a \in B$, this study denotes T'_a as its preferable working time period and E^{req}_a as the total energy required within T'_a. Thus, the constraint for each Type-B appliance is given by:

$$\sum_{t \in T'_a} q^t_a \geq E^{req}_a, \quad a \in B \quad (2)$$

Meanwhile, for some physical conditions, there is usually a limit on the total energy consumption for appliances at each time slot. In practice, such constraints can be used to protect the total energy consumption from exceeding the system capacity. This limit is denoted by E^{max} which can be set by the power grid to impose the following set of constraints on all users' energy scheduling:

$$0 \leq \sum_{a \in A \cup B} q^t_a \leq E^{max}, \quad t \in \mathcal{H} \quad (3)$$

Model of renewable energy generation: In addition, since the generation of renewable energy is a random process, and more importantly, the prediction of its generation is still limited based on the current techniques. Hence, this study models the generation of renewable energy as $w^t = \tilde{w}^t + \phi^t$ (Tarasak, 2011; Wu *et al*., 2010). The first part $\tilde{w}^t$ denotes a predictable value for renewable source generation, which is based on empirical data. The second part ϕ^t denotes the predication error, which is usually random variable and is bounded as $\phi^t \in [-\delta, \delta]$. Here, δ denotes the maximum possible deviation of the estimation. Notice that as an initial step, the current model of this study does not include the energy storage, a promising tool to mitigate the volatility of renewable source. Nevertheless, this study's model helps us focus on analyzing the tradeoff between the energy-acquisition cost and its fluctuation. And this result can be considered as a benchmark performance when the energy storage is further incorporated into the model in future study.

Model of the acquisition-cost of EU: Due to the volatility of renewable energy, there are two different cases the EU will face in its electricity scheduling, i.e., case-1: The instantaneous electricity-provisioning from the renewable supply falls short than the totally scheduled consumption for all the appliances; and case-2: The instantaneous electricity-provisioning from the renewable energy exceeds the totally scheduled consumption for all the appliances. This study will illustrate the corresponding costs for these two cases in depth as follows.

For case-1, the electricity-provisioning from the renewable supply falls short than the totally scheduled consumption for all the appliances, i.e.,:

$$\sum_{a\in A\cup B} q_a^t > w^t$$

Let the random variable:

$$D^t = \left(\sum_{a\in A\cup B} q_a^t - w^t\right) I\left(\sum_{a\in A\cup B} q_a^t - w^t\right)$$

Denote the electricity-deficit due to the short supply of the renewable energy. In other words, D^t represents the amount of electricity that the EU has to purchase from the grid to fulfill its scheduled consumption. Suppose π^t denotes the marginal price for purchasing energy acquisition of EU from the main grid. Therefore, $\pi^t D^t$ denotes the EU's instantaneous acquisition-cost at slot t. Here, indication function $I(x) = 1$ when $x>0$, and $I(x) = 0$ otherwise.

For case-2, the electricity-provisioning from the renewable energy exceeds the totally scheduled consumption for all the appliances, i.e.:

$$\sum_{a\in A\cup B} q_a^t \le w^t$$

Let the random variable:

$$S^t = \left(w^t - \sum_{a\in A\cup B} q_a^t\right) I\left(w^t - \sum_{a\in A\cup B} q_a^t\right)$$

Denote the electricity-surplus due to the over-provisioning of the renewable energy. In other words, S^t represents the instantaneous amount of electricity which the EU wastes. This waste of renewable output usually should be penalized, for instance, Miranda and Hang (2005) state that it is reasonable for the energy users to pay for the waste of available renewable power. Hetzer *et al*. (2008) model the cost for wasting renewable output as a simple penalty function $G(S^t)$. This study assumes this penalty cost function is linear, i.e., denoted by θS^t, where θ is the penalty-cost coefficient. Therefore, θS^t in fact denotes the EU's instantaneous surplus-cost.

Problem formulation: Because of the stochastic nature of renewable energy, the EU's energy acquisition cost is naturally random. Therefore, to optimize the EU's total average energy-acquisition cost as well as its fluctuation, this study formulates the energy scheduling problem as Problem P1:

$$\begin{aligned} \min \quad & \Omega_1 \cdot E\left[\sum_{t\in\mathcal{H}}\left(\pi^t \cdot D^t\right)\right] + \Omega_2 \cdot \mathrm{var}\left[\sum_{t\in\mathcal{H}}\left(\pi^t \cdot D^t\right)\right] \\ & + \Omega_3 \cdot E\left[\sum_{t\in\mathcal{H}}\left(\theta \cdot S^t\right)\right] + \Omega_4 \cdot \mathrm{var}\left[\sum_{t\in\mathcal{H}}\left(\theta \cdot S^t\right)\right] \end{aligned} \tag{4}$$

Subject to: Constraints (1), (2), (3)

decision variables: $q_a^t, \forall a\in A\cup B \forall t\in\mathcal{H}$

In the objective function (4), the first and third part indicate the EU's average acquisition-cost and surplus-cost, respectively, and the second and forth part indicate their fluctuations, respectively.

PROPOSED LAYERED ALGORITHM

In this section, this study proposes an efficient algorithm to solve Problem P1. This study first equivalently transforms Problem P1 to Problem P2 as follows. Specifically, $f_{\Phi^t}(\phi^t)$ denotes the probability density function (PDF) of the random variable ϕ^t and $f_{\Phi^{t_1},\Phi^{t_2}}(\phi^{t_1},\phi^{t_2})$ denotes the joint probability density function. Problem P2 is as follows:

$$\begin{aligned} \min \quad & \Omega_1 \cdot \sum_{t\in\mathcal{H}} \int_{-\delta}^{\min(D^t+\phi^t,\delta)} \pi^t D^t \cdot f_{\Phi^t}(\phi^t)\,d\phi^t + \Omega_2 \cdot \sum_{t_1\in\mathcal{H}} \sum_{t_2\in\mathcal{H}} \int_{-\delta}^{\min(D^{t_1}+\phi^{t_1},\delta)} \int_{-\delta}^{\min(D^{t_2}+\phi^{t_2},\delta)} \pi^{t_1}\pi^{t_2} \cdot D^{t_1} D^{t_2} \cdot f_{\Phi^{t_1},\Phi^{t_2}}(\phi^{t_1},\phi^{t_2})\,d\phi^{t_1} d\phi^{t_2} \\ & - \Omega_2 \cdot \left[\sum_{t\in\mathcal{H}} \pi^t \cdot \int_{-\delta}^{\min(D^t+\phi^t,\delta)} D^t \cdot f_{\Phi^t}(\phi^t)\,d\phi^t\right]^2 + \Omega_3 \cdot \sum_{t\in H} \int_{\max(\phi^t-S^t,-\delta)}^{\delta} \theta S^t \cdot f_{\Phi^t}(\phi^t)\,d\phi^t \\ & + \Omega_4 \cdot \sum_{t_1\in\mathcal{H}} \sum_{t_2\in\mathcal{H}} \int_{\max(\phi^{t}-S^{t},-\delta)}^{\delta} \int_{\max(\phi^{t}-S^{t},-\delta)}^{\delta} \theta^2 \cdot S^{t_1} S^{t_2} \cdot f_{\Phi^{t_1},\Phi^{t_2}}(\phi^{t_1},\phi^{t_2})\,d\phi^{t_1} d\phi^{t_2} \\ & - \Omega_4 \cdot \left[\sum_{t\in\mathcal{H}} \int_{\max(\phi^t-S^t,-\delta)}^{\delta} \theta S^t \cdot f_{\Phi^t}(\phi^t)\,d\phi^t\right]^2 \end{aligned} \tag{5}$$

Subject to: Constraints (1), (2), (3)

decision variables: $q_a^t, \forall a\in A\cup B, \forall t\in\mathcal{H}$

The objective Eq. 5 of Problem P2 strongly depends on the distribution of renewable output and it is usually non-convex in general (Boyd and Vandenberghe, 2004). In particular, the objective function cannot be expressed analytically because it is non-integrable in general. Thus,

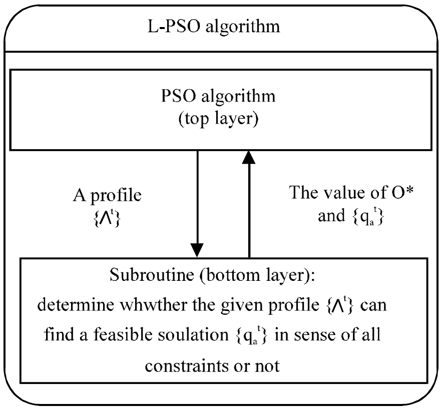

Fig. 2: Illustration of the proposed L-PSO algorithm

this study takes a randomized approach to solve this problem and choose the Particle Swarm Optimization (PSO), one of the artificial intelligence algorithms, which is especially suitable for problems without the objective functions given in analytical forms. The key idea of PSO is as follows. PSO is an artificial intelligence method, which improves a candidate solution iteratively guaranteeing a given measure of quality to optimize a problem (Arumugam *et al.*, 2009; Gao *et al.*, 2009; Lu and Chen, 2011). However, directly using PSO to solve Problem P2 is computationally intractable because the number of decision-variables is very large. For example, suppose there are 10 time slots and 10 appliances for the EU, it will produce 100-dimensional decision variables. So this study proposed a Layer Particle Swarm Optimization (L-PSO), which is shown in Fig. 2. Firstly, this study substitutes the group of $\{q^t_a\}$ with a single decision variable Λ^t, which denotes the total consumption electricity of all appliances at slot t. Then, at the top layer, L-PSO algorithm gets a profile $\{\Lambda^t\}$ by using PSO and updates it until the L-PSO algorithm finds the optimal solution; at the bottom layer, this study proposes a subroutine to determine whether this given profile $\{\Lambda^t\}$ can yield a feasible solution $\{q^t_a\}$ that meets the constraint:

$$\Lambda^t - \sum_{a\in A\cup B} q^t_a \geq 0$$

and constraints (1), (2), (3) or not.

At the top layer of L-PSO algorithm, this study uses PSO algorithm to get a profile $\{\Lambda^t\}$ and updates it until the L-PSO algorithm finds the optimal solution as showed in Algorithm. 1. Specifically, this study assumes each particle $x_i(k)$ denotes a possible profile of $\{\Lambda^t\}$, i.e., the decision variables at the top layer. J(.) represents the fitness function of PSO algorithm. For a given profile $\{\Lambda^t\}$, this fitness function J(.) is determined by Eq. 5 and the value of O* obtained from the output of subroutine at the bottom layer. If $O^*\geq 0$, the fitness function J(.) is evaluated by using Eq. 5. Otherwise, (i.e., $O^*<0$), this study sets $J(.) = J^{max}$, where J^{max} denotes an extremely large value.

At the bottom layer, to determine whether a given profile $\{\Lambda^t\}$ can yield a feasible solution $\{q^t_a\}$, i.e., meeting the constraint $\Lambda^t - \sum_{a\in A\cup B} q^t_a \geq 0$ and constraints (1), (2), (3), or not, this study proposes a subroutine as the follows:

$$O^* = \max z \tag{6}$$

$$\text{subject to: } \Lambda^t - \sum_{a\in A\cup B} q^t_a \geq z, \forall t\in \mathcal{H}$$
$$\text{and constraints (1), (2), (3)}$$
$$\text{decision variables:} q^t_a, \forall a\in A\cup B, \forall t\in \mathcal{H}$$

The above problem (6) in fact is a linear optimization problem and it can be solved via the standard simplex algorithm quickly. Thus, the proposed subroutine outputs the optimal value of which O* indicates whether the given profile $\{\Lambda^t\}$ can yield a feasible electricity scheduling method for all EU's appliances, i.e., meeting the constraint $\Lambda^t - \sum_{a\in A\cup B} q^t_a \geq 0$ and constraints (1), (2) and (3). If $O^*\geq 0$, it means that the given profile $\{\Lambda^t\}$ can find a feasible solution $\{q^t_a\}$. Otherwise, $O^*<0$ it means the given profile $\{\Lambda^t\}$ cannot find a feasible solution $\{q_a^t\}$.

Special model of prediction error of renewable energy: In this subsection, this study further considers a special case of the distribution of prediction error for renewable energy output. Using this special case of distribution, this study obtains the objective function in a closed-form expression. Specifically, this study assumes that estimation error is uniformly distributed within the range of [-δ, δ]. Meanwhile, it also is reasonable that the estimation errors of renewable source output at different slots are independent with each other. Therefore, under this special case, for a given profile $\{\Lambda^t\}$ by PSO, the objective function (5) can be given by the following Eq. 7:

$$F(\{\Lambda^t\}) = \sum_{t\in\mathcal{H}_1} F_1(\Lambda^t) + \sum_{t\in\mathcal{H}_2} F_2(\Lambda^t) + \sum_{t\in\mathcal{H}_3} F_3(\Lambda^t) \tag{7}$$

Specifically, F ({Λ^t}) can be illustrated as the following three different categories.

Category a: $\mathcal{H}_1$ = {t∈$\mathcal{H}$|Λ^t-$\tilde{w}^t$>δ}, the function F_1 (Λ^t)at slot t $\mathcal{H}_1$ is given by:

$$F_1\left(\Lambda^t\right)=\Omega_1\cdot\pi^t(\Lambda^t-\tilde{w}^t)+\frac{1}{3}\Omega_2\cdot(\pi^t)^2\delta^2 \tag{8}$$

Category b: $\mathcal{H}_2$ = {t∈$\mathcal{H}$|Λ^t-$\tilde{w}^t$<-δ}, the function F_2(Λ^t) at slot t ∈ $\mathcal{H}_2$ is given by:

Algorithm 1: PSO Algorithm at the top layer

```
Initialization:
  Initialize the iteration index M, the number of particles' N, the
dimension of time slot H, the learning factors c1, c2
and the maximum and minimum weight
coefficients wmax and wmin;
For i = 1,...,N do
  Randomly initialize particles' position xi (1)
(xi(1) denotes {Λ^1(1), Λ^2(1),...,Λ^H(1)});
  Initialize the local optimal position pi(1) = xi (1);
  Evaluate fitness function J(xi(1)) (based on equation (5) and the value of
O* obtained from the subroutine at the bottom layer):
  If O*≥0 then
  Evaluate J(xi(1)) using equation (5);
  Else
    J(xi(1)) = J^max;
  End if:
Randomly initialize the particles velocity vi(1);
End for:
Initialize the global optimal g(1);
For i = 1,...,N do
    g(1) = p1(1);
    If J(pi(1)≥J(g(1)) then
    g(1) = pi(1);
    Else
    g(1) = g(1)
End if;
End for;
While k≤M do
    w^k = (wmax-wmin)*(M-k)/M+wmin;
  For i = 1,...,N do
vi(k) = w(k)*vi(k-1)+c1*rand(1,H)*(pi(k-1)-xi(k-1))+c2
*rand(1,H)*(g(k-1)-xi(k-1))
Update xi(k) = xi(k-1)+vi(k);
  Evaluate the fitness function J(xi(k)) (based on equation (5) and the value
of O* obtained from the subroutine at the bottom layer):
  If O*≥0 then
    Evaluate J(xi(k)) using equation (5);
    Else
    J(xi(k)) = J^max;
    End if;
    If J(xi(k))≥J(pi(k-1)) then
    pi(k) = xi(k);
    Else
    pi(k) = pi(k-1);
    End if;
    If J(pi(k))≥J(g(k-1)) then
    g(k) = g(k-1);
    Else
    g(k) = pi(k-1);
    End if;
    End for;
  k = k+1;
End while
```

$$F_2\left(\Lambda^t\right)=\Omega_3\cdot\theta\cdot(\tilde{w}^t-\Lambda^t)+\frac{1}{3}\Omega_4\cdot\theta^2\delta^2 \tag{9}$$

Category c: $\mathcal{H}_3$ = {t∈$\mathcal{H}$|-δ≤Λ^t-$\tilde{w}^t$≤δ}, the function F_3(Λ^t) at slot t∈$\mathcal{H}_3$ is given by function (10):

$$\begin{aligned}F_3\left(\Lambda^t\right)=&\Omega_1\cdot\frac{\pi^t}{2\delta}\cdot\left[\frac{1}{2}(\Lambda^t-\tilde{w}^t)^2+\delta(\Lambda^t-\tilde{w}^t)+\frac{\delta^2}{2}\right]+\Omega_2\cdot\frac{(\pi^t)^2}{2\delta}\cdot\left[\frac{1}{3}\left(\Lambda^t-\tilde{w}^t\right)^3+\delta\left(\Lambda^t-\tilde{w}^t\right)^2+\delta^2\left(\Lambda^t-\tilde{w}^t\right)+\frac{1}{3}\delta^3\right]\\&-\Omega_2\cdot\frac{\left(\pi^t\right)^2}{(2\delta)^2}\cdot\left[\frac{1}{2}\left(\Lambda^t-\tilde{w}^t\right)^2+\delta\left(\Lambda^t-\tilde{w}^t\right)+\frac{1}{2}\delta^2\right]^2+\Omega_3\cdot\frac{\theta}{2\delta}\cdot\left[\frac{1}{2}\left(\tilde{w}^t-\Lambda^t\right)^2+\delta\left(\tilde{w}^t-\Lambda^t\right)+\frac{\delta^2}{2}\right]\\&+\Omega_4\cdot\frac{\theta^2}{2\delta}\cdot\left[\frac{1}{3}\left(\tilde{w}^t-\Lambda^t\right)^3+\delta\left(\tilde{w}^t-\Lambda^t\right)^2+\delta^2\left(\tilde{w}^t-\Lambda^t\right)+\frac{1}{3}\delta^3\right]-\Omega_4\cdot\frac{\theta^2}{(2\delta)^2}\cdot\left[\frac{1}{2}\left(\tilde{w}^t-\Lambda^t\right)^2+\delta\left(\tilde{w}^t-\Lambda^t\right)+\frac{1}{2}\delta^2\right]^2\end{aligned} \tag{10}$$

SIMULATION RESULTS

Here, this study provides numerical results to show the performance of our L-PSO and the tradeoff between the EU's average cost and its fluctuation. In this numerical example, the scheduling horizon is given by $\mathcal{H}$ = {1, 2, 3, 4, 5, 6}, the predictive value of renewable energy is given by $\tilde{w}$ = {2, 4, 3, 5, 3, 5} KWH and the parameter of the estimation error is given by δ = 1. Then assume that the EU has two different Type-A appliances denoted by a_1, a_2 and two different Type-B appliances denoted by b_1, b_2. And the group of energy consumption per slot for a_1, a_2 is given by $r_{a_1}=\{0,1,1,1,1,0\}$ KWH and $r_{a_2}=\{0.5,0.5,0.5,0.5,0.5,0.5\}$ KWH, the minimum energy consumption for the whole working period of b_1, b_2 is given by $E_{b_1}^{req}=10\text{KWH}$, $E_{b_2}^{req}=13\text{KWH}$, the group of working period for b_1, b_2 is given by $T_{b_1}^{'}=\{3,4,5\}$, $T_{b_2}^{'}=\{4,5,6\}$. The maximum energy consumption for all appliances of EU is given by E^{max} = 12 KWH. In addition, the algorithm parameters are set as N = 30, c_1 = c_2 = 1, w_{max} = 0.9, w_{min} = 0.4. The detailed setup is presented in Table 1.

Performance of our L-PSO algorithm: Figure 3 and Fig. 4 show that the consumed computational time for

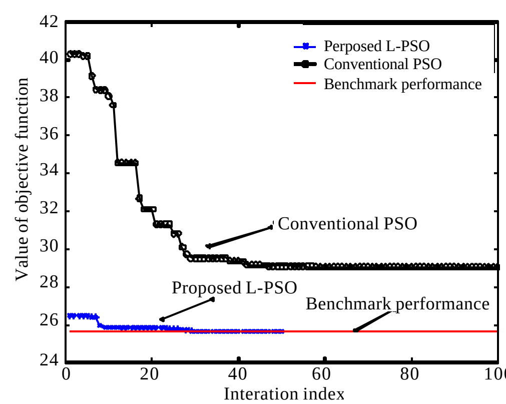

Fig. 3: Illustration of the complexity of L-PSO under θ = 0.8

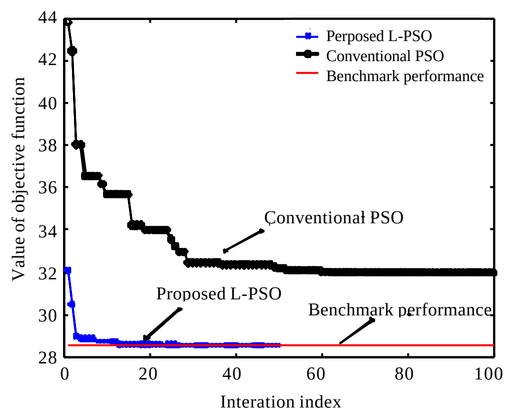

Fig. 4: Illustration of the complexity of L-PSO under $\theta = 1$

Table 1: Detailed setup for numerical example

The scheduling horizon	$\mathcal{H} = \{1, 2, 3, 4, 5, 6\}$
The electricity price	$\pi = \{\$1.5, \$1.2, \$1.1, \$2.0, \$1.0, \$1.7\}$
The predictive value of renewable energy	$w = \{2, 4, 3, 5, 3, 5\}$ KWH, $\delta = 1$
For Type-A appliances	$r_{a1} = \{0, 1, 1, 1, 1, 0\}$KWH, $r_{a2} = \{0.5, 0.5, 0.5, 0.5, 0.5, 0.5\}$ KWH
For type-B appliances	$E_{b_1}^{req} = 10$ KWH, $T'_{b_1} = \{3, 4, 5\}$
	$E_{b_2}^{req} = 13$ KWH, $T'_{b_2} = \{4, 5, 6\}$
For the EU	$E^{max} = 12$ KWH
The algorithm parameters	$N = 30, c_1 = c_2 = 1, w_{max} = 0.9, w_{min} = 0.4$

Table 2: Average computation time at different precision (take the average of 30 tests)

Precision	1%	2%	3%	4%
Proposed L-PSO	81.33s	60.75s	34.81s	29.46s
(the successful rate)	(100%)	(100%)	(100%)	(100%)
Conventional PSO	181.13s	123.63s	49.96s	32.13s
(the successful rate)	(67%)	(70%)	(87%)	(90%)

this proposed algorithm to reach a benchmark performance. Specially, this study uses a commercial solver Matlab, to generate the optimal solution for Problem P2. The results in Fig. 3 and 4 show that the proposed L-PSO can quickly reach the optimal solution in comparison the conventional PSO. Or in other words, to get the solution with same prescribed accuracy, L-PSO can save computational time compared to conventional PSO method.

From Fig. 3 and 4, this study can also find that L-PSO algorithm has advantages for solving this energy scheduling problem at different situations $\theta = 0.8$ and $\theta = 1$. To further verify this result, this study does more simulations at different situations by changing the penalty cost coefficient θ and the weight-factor Ω_2. Figure 5 shows that given the same value of maximum iteration limit (i.e., $M = 25$), L-PSO can obtain a solution

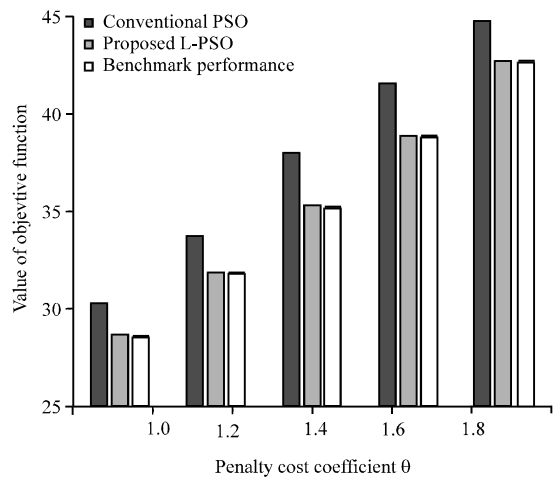

Fig. 5: Effect of the algorithm at different scenes by tuning the penalty cost coefficient θ

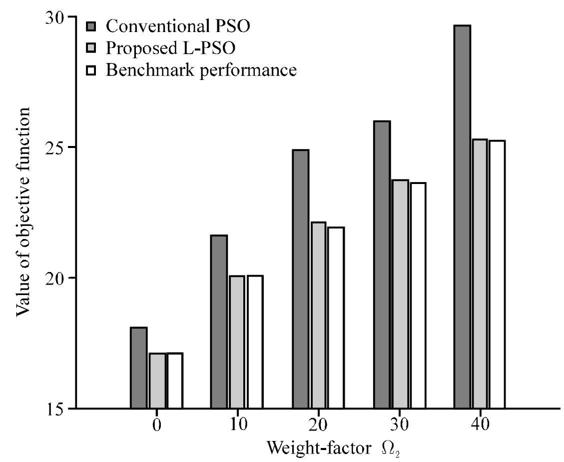

Fig. 6: Effect of the algorithm at different scenes by changing the weight-factor Ω_2

more close to the benchmark one on comparison with the conventional PSO method. Figure 6 shows the similar results by changing the weighting-factor Ω_2.

Table 2 shows the computational time consumed by L-PSO to reach a prescribed accuracy. Here, x% denotes the prescribed accuracy for the solution. In particular, the simulation sets the limit on the running time as 400 sec. If the algorithm cannot reach a solution with a prescribed accuracy within 400 sec, this study considers that a failure occurs for the algorithm. Thus, this study can take account of the successful rate that L-PSO reaches the solution with the prescribed accuracy. The results show that L-PSO performs much better than the conventional PSO in both computational time and successful-rate. Notice that even with a medium size of

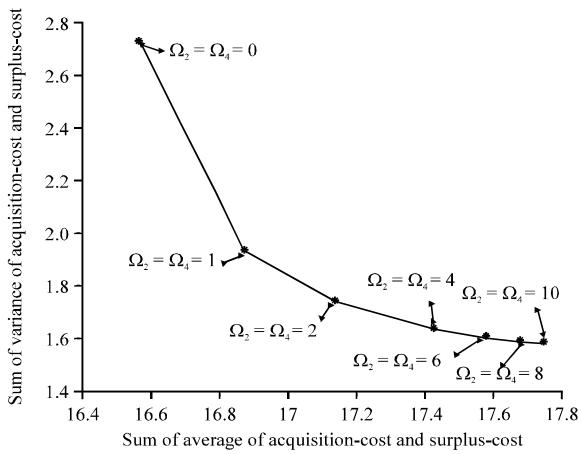

Fig. 7: Sum of the average acquisition-cost and surplus-cost vs. Sum of the variance of acquisition-cost and surplus-cost at different weighting-factors $\Omega_2 = \Omega_4$, with the weighting-factors $\Omega_1 = \Omega_3 = 1$

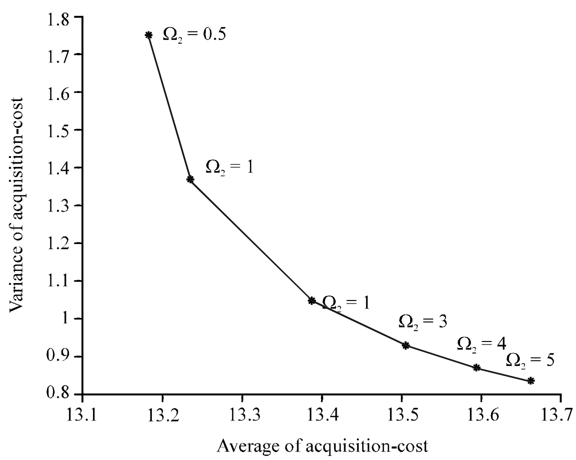

Fig 8: Average acquisition-cost and its variance at different weighting-factor Ω_2 with the weighting-factors $\Omega_1 = \Omega_3 = \Omega_4 = 1$

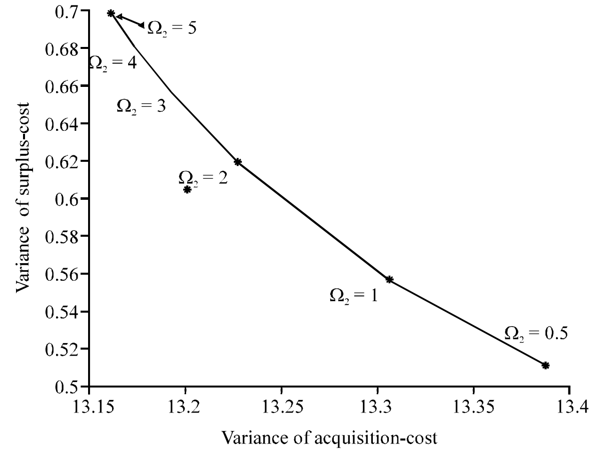

Fig 9: Variance of acquisition-cost vs. variance of surplus-cost at different weighting-factor Ω_2, with the weight-factors $\Omega_1 = \Omega_3 = \Omega_4 = 1$

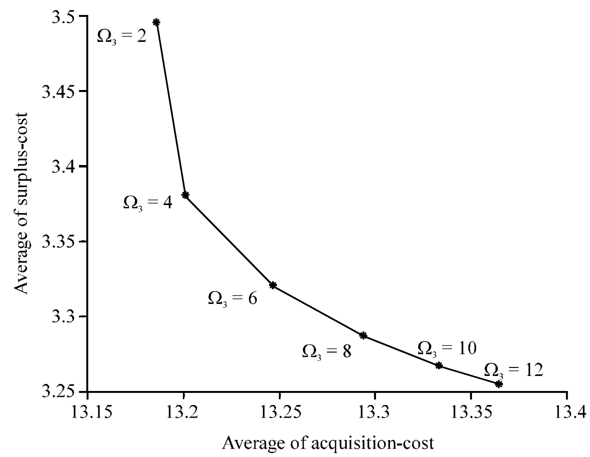

Fig 10: Average acquisition-cost vs. Average surplus-cost at different weight-factor Ω_3 with the weighting-factors $\Omega_1 = \Omega_2 = \Omega_4 = 1$

example the simulation considered, the conventional PSO stills cannot perform well frequently.

All the above numerical results show that our proposed PSO is computationally efficient to reach the optimal electricity scheduling. The reason can be attributed to the layering idea.

Tradeoff between the average energy cost and its fluctuation: In this subsection, this study shows the tradeoff between user's average energy cost and its fluctuation. Figure 7 shows that, by changing the weighting-factors $\Omega_2 = \Omega_4$ from 0 to 10, there exists a clear tradeoff between user's average electricity cost (which includes its average acquisition-cost and surplus-cost) and its corresponding fluctuation. This result in fact matches our intuition very well. Through tuning the weighting-factors, the user is able to flexibly trade off its preferences between a low average cost and a low fluctuation.

Figure 8 further shows that there exists a tradeoff between the EU's average acquisition-cost and its fluctuation. Through adjusting the weighting-factor, the EU can adjust its preference between these two aspects.

In addition, Fig. 9 shows that by tuning the weighting-factor Ω_2, there also exists a tradeoff between the variance of acquisition-cost and the variance of surplus-cost. The acquisition-cost's fluctuation increases, the surplus-cost's fluctuation reduces. Moreover, Fig. 10

shows that by tuning the weighting-factor Ω_3, there exists a tradeoff between the average acquisition-cost and the average surplus-cost, i.e., when increasing the EU's average acquisition-cost, the average surplus-cost reduces.

CONCLUSION

This study proposes to jointly optimize the EU's average energy-scheduling cost as well as its fluctuation based on user's preference between these two aspects. This problem is formulated as a non-convex optimization problem and this study proposes an efficient Layered Particle Swarm Optimization (L-PSO) to determine the EU's optimal scheduling of electricity consumption for its appliances. In particular, compared to the conventional PSO algorithm, our proposed L-PSO can save the computational complexity significantly. In addition, this study’s extensive numerical results show how the EU can trade off between benefiting from the renewable supplies and suffering from the associated fluctuation through tuning the weighting-factors. The future study is to further incorporate the energy storage into our model and investigate how it helps mitigate the fluctuation of the EU's electricity-scheduling cost.

ACKNOWLEDGMENT

This study is supported, in partial, by Qianjiang Talent Project (QJD1202011), ZLT-MCNS (2012R10011-06), ZJNSFC (Z1110893).

REFERENCES

Arumugam, M.S., M.V.C. Rao and A.W.C. Tan, 2009. A novel and effective particle swarm optimization like algorithm with extrapolation technique. Applied Soft Comput., 9: 308-320.

Boyd, S. and L. Vandenberghe, 2004. Convex Optimization. Cambridge University Press, Cambridge, UK.

Conejo, A.J., J.M. Morales and L. Baringo, 2010. Real-time demand response model. IEEE Trans. Smart Grid, 1: 236-242.

Frye, W. and Cisco Internet Business Solutions Group, 2008. Transforming the electricity system to meet future demand and reduce greenhouse gas emissions. CISCO White Paper. http://www.cisco.com/web/about/ac79/docs/ Smart_Grid_WP_1124aFINAL.pdf

Gao, X.Y., L.Q. Sun and D.S. Sun, 2009. An enhanced particle swarm optimization algorithm. Inform. Technol. J., 8: 1263-1268.

Ghader, S.F., M.A. Azadeh and S. Mohammadzadeh, 2006. Modeling and forecasting the electricity demand for major economic sectors of Iran. Inform. Technol. J., 5: 260-266.

Hetzer, J., D.C. Yu and K. Bhattarai, 2008. An economic dispatch model incorporating wind power. IEEE Trans. Energy Convers., 23: 603-611.

Jiang, L. and S. Low, 2011a. Multi-period optimal procurement and demand responses in the presence of uncertain supply. Proceedings of the 50th IEEE Conference on Decision and Control and European Control, December 12-15, 2011, Orlando, FL, USA., pp: 4348-4353.

Jiang, L. and S. Low, 2011b. Real-time demand response with uncertain renewable energy in smart grid. Proceedings of the 49th Annual Allerton Conference on Communication, Control and Computing, September 28-30, 2011, Monticello, IL, USA., pp: 1334-1341.

Li, N., L. Chen and S.H. Low, 2011. Optimal demand response based on utility maximization in power networks. Proceedings of the IEEE Power and Energy Society General Meeting, July 24-29, 2011, Michigan, USA., pp: 1-8.

Lu, H. and X. Chen, 2011. A new particle swarm optimization with a dynamic inertia weight for solving constrained optimization problems. Inform. Technol. J., 10: 1536-1544.

Miranda, V. and P.S. Hang, 2005. Economic dispatch model with fuzzy wind constraints and attitudes of dispatchers. IEEE Trans. Power Syst., 20: 2143-2145.

Mohsenian-Rad, A., V.W.S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, 2010a. Autonomous demand-side management based on game-theoretic energy comsumption scheduling for the future smart grid. IEEE Trans. Smart Grid, 1: 320-331.

Mohsenian-Rad, A.H. and A. Leon-Garcia, 2010b. Optional residential load control with price prediction in real-time electricity pricing environments. IEEE Trans. Smart Grid, 1: 120-133.

Pedrasa, M.A.A., T.D. Spooner and I.F. MacGill, 2010. Coordinated scheduling of residential distributed energy resources to optimize smart home energy services. IEEE Trans. Smart Grid, 1: 134-143.

Pothamsetty, V. and S. Malik, 2009. Leveraging intelligent communications to transform the power infrastructure. CISCO Public Information. http://www.cisco.com/web/about/citizenship/environment/docs/sGrid_wp_c11-532328.pdf

Samadi, P., H. Mohsenian-Rad, R. Schober and V.W.S. Wong, 2010. Advanced demand side management for the future smart grid using mechanism design. IEEE Trans. Smart Grid, 3: 1170-1180.

Tarasak, P., 2011. Optimal real-time pricing under load uncertainty based on utility maximization for smart grid. Proceedings of the IEEE International Conference on Smart Grid Communications, October 17-20, 2011, Brussels, Belgium, pp: 321-326.

U.S. Department of Energy, 2009. The smart grid: An introduction. http://energy.gov/sites/prod/files/oeprod/DocumentsandMedia/DOE_SG_Book_Single_Pages%281%29.pdf

Wu, C., A.H. Mohsenian-Rad and J. Huang, 2010. Wind power integration via aggregator-consumer coordination: A game theoretic approach. Proceedings of the IEEE PES Innovative Smart Grid Technologies Conference, October 11-13, 2010, Gothenburg, Sweden, pp: 1-6.