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Solving the Optimal Real-time Pricing of Smart Grid to Maximize Utility based on Distributed and Particle Swarm Algorithms

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Abstract

This paper considers a smart power infrastructure where multiple users share a common energy source. Each electricity meter is equipped with an energy consumption controller, and each user has an electricity meter. Electric meters are connected to various infrastructure and networks. This enables two-way communication between smart meters. Considering the importance of energy pricing as an important tool for formulating efficient demand-side management strategies, this paper proposes a new real-time pricing algorithm suitable for future smart grids, focusing on the interaction between smart meters and energy providers, including users through exchanges Control messages for energy consumption and real-time price information. First, users' preferences and their energy consumption patterns are analytically modeled in the form of carefully chosen utility functions based on microeconomic concepts. Second, this paper proposes a distributed algorithm that automatically manages the interaction between smart meters and energy providers' ECC units. The algorithm calculates the lowest energy consumption level for each user and maximizes the total utility of all users. Finally, we show that through the proposed real-time pricing interaction, energy providers can encourage the development of some desirable consumption patterns among users. The simulation results of this paper confirm that the proposed distributed algorithm and particle swarm algorithm can benefit both users and energy providers.

Keywords

Distributed Algorithms; Particle Swarm Optimization; Electricity Meter Pricing.

1. Introduction

Electricity is currently provided through an infrastructure consisting of utility companies, power plants, and transmission lines that serve millions of customers. For example, the U.S. power grid includes more than 3,100 power companies operating more than 10,000 power plants, and approximately 158,000 miles of high-voltage transmission lines bring energy to more than 131 million customers [1]. The dependence of almost all parts of the industrial sector, as well as the lives of our residents, on electrical energy makes this vast infrastructure a strategic entity.

Given the increase in customer expectations, both in terms of quality and quantity [1] , energy resources are very limited, and developing and utilizing new resources is a long and expensive process. The reliability of the grid has been put at risk and new methods need to be developed. Improve grid efficiency. Currently, most buildings use electricity in an inefficient manner (e.g. due to poor thermal insulation), which results in a huge waste of natural resources. Additionally, the resulting demand for new types of electricity facilities, such as plug-in hybrid electric vehicles (PHEVs), may double average household loads, further increasing the need to develop new demand-side management (DSM) approaches. There is a wide range of DSM techniques, such as voluntary load management procedures [3][5] and direct load control [6]. However, smart pricing is considered one of the most common tools that can encourage users to spend wisely and be more efficient. Due to the recent increase in energy prices, users are more willing to improve the insulation conditions of buildings or try to plan energy consumption for high-load household appliances during off-peak hours. DSM is a tool that has been considered since the early 1980s [7]-[11]. Broad categories of load shaping objectives include peak shaving, load variation, valley filling, strategic protection, and flexible load shaping [7]. For example, peak shaving involves direct load control of utility customer equipment to reduce peak loads. Several pricing schemes have been proposed in the smart grid literature. Generally speaking, parity pricing, peak load pricing and adaptive pricing are one of the most popular pricing methods and have been widely used [12]-[15]. Parity pricing is a method by which utilities publish fixed prices for all periods. In power peak and valley load pricing, the predetermined cycle is divided into several time periods, and the price value of each time period is announced at the beginning of operation. In adaptive pricing, on the other hand, instead of announcing the predetermined price for each period of operation at the beginning of the day, the exact price value of each period is calculated in real time and announced only at the beginning of each period of operation. Obviously, in this approach, the realization of random events and user reactions to previous prices will affect prices during future runs [12].

According to a report by the U.S. Department of Energy [16], a smart grid is a power delivery system enhanced by communication facilities and information technology to improve customer service and clean the environment, making the grid operation more efficient and reliable. By utilizing the two-way communication capabilities of smart meters, it becomes possible to replace the current power system with a smarter infrastructure [17] . Based on this and considering the importance of demand-side management, this paper focuses on the real-time interaction between users and energy providers and proposes a new real-time pricing algorithm suitable for future smart grids.

2. Model Establishment

This article assumes a power system consisting of energy suppliers, power users and power regulators. Each user is equipped with an Energy Consumption Controller (ECC) unit. The role of ECC is to control power consumption and coordinate the relationship between each user and other users and energy suppliers. All ECC units are connected to each other and to energy suppliers through communication infrastructure such as local area networks.

The expected time period of user operation is divided into time slots, where $K \triangleq |K|$ is $|K|$ the set of all time slots. This division can be based on user behavior and their electricity demand patterns: peak load periods, off-peak load periods and normal load periods. Furthermore, let N denote the set of all users, where $N \triangleq |N|$, for each user $i \in N$, let denote x_i^k the power consumed by the user i during the time slot . k For each user $i \in N$ and each time period $k \in K$, we define a power consumption interval I_i^k :

$$I_i^k \triangleq \left[m_i^k, M_i^k \right] \tag{1}$$

And the power consumption x_i^k must be met $m_i^k \le x_i^k \le M_i^k$. m_i^k and M_i^k represent the user i 's minimum and maximum power consumption, respectively. The lowest power consumption level may represent the load of an appliance such as a refrigerator that always needs to be on during the day. The maximum power consumption level may also represent the total power consumption level of a household appliance assuming all appliances are turned on.

The regulator ensures that energy suppliers will provide a minimum capacity to meet the $L_k^{\min}$ minimum electricity demand of all users during each period.

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$$L_k^{\min} \triangleq \sum_{i \in N} m_i^k, \qquad \forall k \in K \tag{2}$$

The amount of electricity generated L_k in each period is $k \in K$ expressed in, and may differ between periods. We will also $L_k^{\max}$ define as $k \in K$ the maximum power generation in each period.

2.1. User Preferences and Utility Functions

Each user in the power system is an entity that can operate independently. The energy needs of each user may vary based on different parameters. For example, we can consider the time of day, climate conditions, and electricity prices. Energy requirements also depend on the type of user. For example, residential users may respond differently to the same price than industrial business users. Here, the utility function in economics is used to analyze and model the different responses of different users. In fact, the behavior of different users can be modeled by their different choices of utility functions. For all users, our utility function is expressed as $U(x,\omega)$, where x is the user's energy consumption level and ω is a parameter that may vary between users and at different times of the day. For each user, the utility function represents the level of satisfaction achieved by the user as a function of its power consumption. We assume that the utility function satisfies the following properties:

$$\frac{\partial U(x,\omega)}{\partial x} \geq 0 \tag{3}$$

$$V(x,\omega) \triangleq \frac{\partial U(x,\omega)}{\partial x} \geq 0 \tag{4}$$

Formulas (3) and (4) are marginal utility.
User marginal utility is a non-increasing function, such as formula (5):

$$\frac{\partial U(x,\omega)}{\partial x} \leq 0 \tag{5}$$

In general, the utility function is a concave function, and user satisfaction will gradually become saturated. Although the category of utility functions that satisfy equations (3) and (5) is very large, it is very convenient to have linear marginal benefits.
We must be able to rank customers based on their utility. In the formula, we assume that for a fixed level of consumption x, the larger
ω means large $U(x,\omega)$ and can be expressed as:

$$\frac{\partial U(x,\omega)}{\partial x} > 0 \tag{6}$$

We assume there is no general expectation that power consumption will bring any benefit, so:

$$U(0,\omega) = 0, \qquad \forall \omega > 0 \tag{7}$$

A selection of various utility functions is widely used in existing literature on communications and networking. However, recent reports indicate that the behavior of advanced users can also be accurately modeled by certain utility functions.

$$U(x,\omega)=\begin{cases}\omega x-\dfrac{\alpha}{2}x^2 & if \quad 0\le x\le\dfrac{\omega}{\alpha}\\ \dfrac{\omega}{\alpha} \quad if & x\ge\dfrac{\omega}{\alpha}\end{cases} \tag{8}$$

where α is a predetermined parameter.

Users who Px consume kW of electricity at a rate of P dollars/kWh within a specified number of hours are charged x USD per hour. Therefore, the welfare of each user can be simply expressed as:

$$W(x,\omega)=U(x,\omega)-Px \tag{9}$$

where $W(x,\omega)$ is the user's welfare function, $U(x,\omega)$ is the user's utility function, Px is the cost imposed by the energy provider on the user, and x is the user's electricity consumption. For each published price value P, each user tries to adjust his or her power consumption x to maximize his or her welfare, which can be achieved by setting the derivative of equation (9) to zero, which means that at the optimal consumption level Below, the marginal revenue to the user will be equal to the published price.

2.2. Energy Cost Model

Let the expression of cost be $C_k(L_k)$, which represents $k\in K$ the cost of unit energy consumption provided by the energy provider in each time slot. L_k We make the following assumptions:

Assumption 1:The cost function increases in the energy capacity provided. That is, for each $k\in K$, therefore:

$$C_k\left(\hat{L}_k\right)\le C_k\left(\tilde{L}_k\right),\quad \forall\hat{L}_k\le\tilde{L}_k \tag{10}$$

Assumption 2:The cost function is a convex function. For $k\in K$, $0\le\theta\le 1$, and $\hat{L}_k,\tilde{L}_k\ge 0$, therefore:

$$C_k\left(\theta\hat{L}_k+(1-\theta)\tilde{L}_k\right)\le\theta C_k\left(\hat{L}_k\right)+(1-\theta)C_k\left(\tilde{L}_k\right) \tag{11}$$

Piecewise linear function and quadratic function are two example cost functions that satisfy Assumption 1 and Assumption 2. In this article, we consider the quadratic cost function:

$$C_k(L_k)=a_kL_k^2+b_kL_k+c_k \tag{12}$$

Among them $a_k > 0$, $b_k, c_k \geq 0$, are all predetermined parameters.

3. Problem Description and Analysis

3.1. Problem Description

In this section, we formulate the interaction between electricity users and energy suppliers as an optimization problem and analyze the existence and uniqueness of the solutions. In our model, energy suppliers publish electricity prices in real time based on total load demand.

From the perspective of social equity, it is hoped to utilize the available capacity provided by energy suppliers in such a way that the total utility of users is maximized and the energy consumption of suppliers is minimized. However, each subscriber will choose its consumption level to maximize its welfare function introduced in (9). These individual optimal consumption levels may not be socially optimal for the general prices published by energy suppliers. In order to align these individual optimal consumption levels with the social optimal situation, we need to take as the objective function the sum of all utility functions minus the costs imposed on energy suppliers, while the consumption levels of all users are determined by the limited available generation capacity. Coupling. With centralized control over all subscribers and complete information about subscriber needs, effective energy consumption planning can be described as a solution to the following problems:

$$\begin{aligned} \max_{\substack{x_i^k \in I_i^k, L_k^{\min} \leq L_k \leq L_k^{\max}, \\ i\in N, k\in K}} imize \quad & \sum_{k\in K} \sum_{i\in N} U\left(x_i^k, \omega_i^k\right) - C_k\left(L_k\right) \\ st. \quad & \sum_{i\in N} x_i^k \leq L_k, \forall k \in K \end{aligned} \tag{13}$$

in $U\left(x_i^k, \omega_i^k\right)$ formula (8) , and the definition is $C_k(L_k)$ as shown in ω_i^k formula (12) , which is the user's i parameter ω in the period k .

The problem proposed in (13) is a concave function maximization problem that can be solved in a central manner using convex programming techniques such as the interior point method (IPM).

3.2. Problem Analysis

We note that equation (13) can $k \in K$ be solved independently for each time slot. In other words, for each fixed time slot $k \in K$, we have the following optimization problem:

$$\begin{aligned} \max_{x_i^k \in I_i^k, i\in N, L_k^{\min} \leq L_k \leq L_k^{\max}} imize \quad & \sum_{i\in N} U\left(x_i^k, \omega_i^k\right) - C_k\left(L_k\right) \\ st. \quad & \sum_{i\in N} x_i^k \leq L_k \end{aligned} \tag{14}$$

Problem (14) is a convex problem and can be easily solved centrally. In practice, this problem must be solved in a distributed manner. Although the objective function in x_i^k (14) is further separable in x_i^k and , the variables L_k and are coupled L_k by the imposed constraint that the total consumed power cannot exceed the available capacity in (14).

For the original problem (14), the Lagrangian is defined as:

$$\begin{aligned} \iota\left(x, L_k, \lambda^k\right) = & \sum\nolimits_{i \in N} U\left(x_i^k, \omega_i^k\right) - C_k\left(L_k\right) \\ & -\lambda^k\left(\sum\nolimits_{i \in N} x_i^k - L_k\right), \\ & = \sum\nolimits_{i \in N}\left(U\left(x_i^k, \omega_i^k\right) - \lambda^k x_i^k\right) \\ & +\lambda^k L_k - C_k\left(L_k\right), \end{aligned} \tag{15}$$

where λ^k is the Lagrange multiplier, $x = \left(x_i^k, i \in N\right)$ used for fixation $k \in K$. Due to the separability of the first term of Lagrangian, we can write the objective function of the dual optimization problem as:

$$\begin{aligned} D\left(\lambda^k\right) = & \underset{x_i^k \in I_i^k, i \in N, L_k^{\min} \le L_k \le L_k^{\max}}{\max\text{imize}} \iota\left(x, L_k, \lambda^k\right) \\ = & \sum\nolimits_{i \in N} B_i^k\left(\lambda^k\right) + S_k\left(\lambda^k\right) \end{aligned} \tag{16}$$

In:

$$B_i^k\left(\lambda^k\right) = \underset{x_i^k \in I_i^k}{\max imize} U\left(x_i^k, \omega_i^k\right) - \lambda^k x_i^k \tag{17}$$

$$S_k\left(\lambda^k\right) = \underset{L_k^{\min} \le L_k \le L_k^{\max}}{\max imize} \quad \lambda^k L_k - C_k\left(L_k\right) \tag{18}$$

Double question:

$$\underset{\lambda^k > 0}{\min\text{imize}} \quad D\left(\lambda^k\right) \tag{19}$$

in equation (16) $D(\lambda^k)$ can be decomposed into N separable sub-problems of the form (17), which can be solved by the user, and the other sub-problem is of the form (18), which can be solved by the user for the energy supplier.

We can show that the strong duality holds, and we can solve the dual problem (19) instead of the primal problem (14). In this case, we can obtain λ^{k*} a solution to the dual problem, and each individual user and energy supplier can simply solve their own local optimization problem determined by (17) and (18), obtaining and x_i^{k*} respectively L_k^*.

(17) with (9) that each individual user has to solve, and introduce the welfare of each user, we can understand the key idea that led us to propose a real-time pricing algorithm. In fact, if the energy supplier is able to $P = \lambda^{k*}$ charge users at a rate of, and each user tries to maximize his own welfare function, then strong duality will guarantee that the total power consumption does not exceed the provided capacity.

4. Distributed Algorithms and Heuristic Algorithms

4.1. Distributed Algorithm

We explained in the previous section that by charging the user for λ^{k*} the solution to the dual problem, we can implement the solution to the original problem (14). The dual problem can be solved iteratively using gradient projection methods, in which case we have:

$$\lambda_{t+1}^{k} = \left[\lambda_t^k - \gamma \frac{\partial D\left(\lambda_t^k\right)}{\partial \lambda^k} \right] + \\ = \left[\lambda_t^k + \gamma \left(\sum_{i \in N} x_i^{k*}\left(\lambda_t^k\right) - L_k^*\left(\lambda_t^k\right) \right) \right]^+ \tag{20}$$

where $t \in T$ is T the set of time instances updated by the energy supplier. λ^k Here, $x_i^{k*}(\lambda_t^k)$ are the local optimizers of $L_k^*(\lambda_t^k)$ (17) and are the local optimizers of the given λ_t^k (18), respectively. Additionally, λ_t^k is $t \in T$ the value λ in the instance and λ^k is the step size. The interaction between energy providers and users is shown in Figure 1.

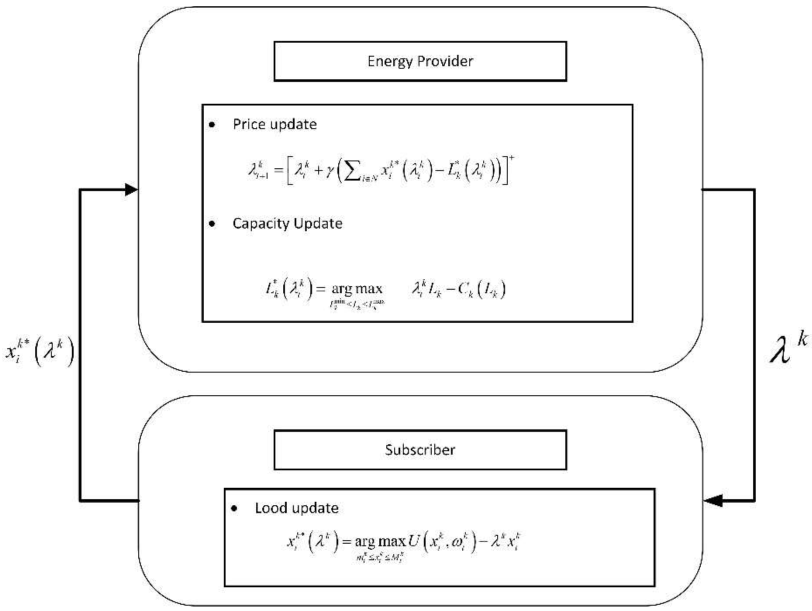

Figure 1. Illustration of the operation of the proposed algorithm and theinteractions between the energy provider and subscribers in the system.

The distributed algorithms for each user and energy provider are summarized in Algorithms 1 and 2 respectively. Consider Algorithm 1. In line 1, each subscriber starts with its initial conditions, assumed to be random. Then, the loop on lines 2 to 6 describes each subscriber's λ^k response to the newly announced price. In this loop, each subscriber receives the new value at line λ^k 3 and solves the local problem (17) to obtain the new value corresponding to line 4. λ^k value of optimal consumption $x_i^{k*}(\lambda_t^k)$. On line 5, the user $x_i^{k*}(\lambda_t^k)$ communicates the new value of to the energy provider. We note that in each epoch $k \in K$, users only apply their new loads after the algorithm has converged.

Algorithm1: Executed by each subscriber $i \in N$.

1:Initialization

2: **for each** $t \in T$

3: Receive the new value of λ^k from energy provider.

4: Update the consumption value $x_i^{k*}(\lambda_t^k)$ by solving(17).

5: Communicate the updated $x_i^{k*}(\lambda_t^k)$ to energy provider.

6: **edn for**

In Algorithm 2 , the energy provider starts with random initial conditions in line 1 . The loop in lines 2 to 11 continues during the system's run cycle. In this loop, the energy provider is updated in each $t \in T$ instance in lines λ^k 4 and 5 . It further calculates $L_k^*(\lambda_t^k)$ a new value that maximizes its welfare and updates its information about the total consumption level of the system from 7 to 9.

Algorithm2: Executed by the energy provider.
1:Initialization.
2:repeat.
3: **if** time $t \in T$.
4: Compute the new value of λ^k using (20).
5: Broadcast the new value of λ^k to all the subscribers.
6: **else.**
7: Update the capacity value $x_i^{k*}(\lambda_t^k)$ by solving(18).
8: Receive $x_i^{k*}(\lambda_t^k)$ from all the subscribers $i \in N$.
9: Update the total load $\sum_{i \in N} x_i^{k*}(\lambda^k)$ accordingly.
10: **end**
11: **until** end of intended period.

We note that network utility maximization has been successfully applied to computer networks. The problem formulation in this section is similar to the congestion control problem in the Internet. However, the pricing algorithm in this paper differs from the Internet rate allocation problem in two aspects: (a) the capacity can be adjusted by the energy provider and may change periodically with a fixed capacity constraint; (b) we Consider the energy costs imposed on energy suppliers and formulate the problem as utility maximization and cost minimization.

4.2. Heuristic Algorithm-Particle Swarm Optimization

Particle Swarm Optimization (PSO) treats each individual as a particle in a three-dimensional space and gives it a certain initial velocity to fly randomly. The particles will change with reference to the optimization results of other particles, thereby continuously seeking optimization. Even so, the PSO algorithm gradually moves individuals to better areas based on each particle's adaptability to the environment, and finally searches and finds the optimal solution to the problem.

In the PSO algorithm, particles represent potential solutions to the problem and also represent a fitness value. Suppose there are D particles forming a group in a t one-dimensional search.

The position m of space.The position of m the particle at the first iteration i is expressed as $X_i(t)=(x_{i1}(t),x_{i2}(t),\cdots,x_{iD}(t))$ and the corresponding flight speed is expressed as. When $V_i(t)=(v_{i1}(t),v_{i2}(t),\cdots,v_{iD}(t))$ starting to execute the PSO algorithm, first initialize m the position and speed of the particles, and then Optimization through iterative calculation: There are two extreme values in the algorithm during the calculation process. One extreme value is the optimal solution searched so far by the particle itself, which is called the local optimal value, expressed as; the other $P_i(t)=(p_{i1}(t),p_{i2}(t),\cdots,p_{iD}(t))$ extreme value is the entire particle The optimal solution found so far by the group is called the global optimal value and is expressed as $P_g(t)=(p_{g1}(t),p_{g2}(t),\cdots,p_{gD}(t))$.

Specifically, during $t+1$ the iterative calculation, the particles i will be updated according to the following formula:

$$v_{ik}(t+1) = \omega v_{ik}(t) + c_1 \times rand1(0,1) \times (p_{ik}(t) - x_{ik}(t))$$
$$c_2 \times rand2(0,1) \times (p_{gk}(t) - x_{ik}(t)) \quad \text{(twenty one)}$$

$$x_{ik}(t+1) = x_{ik} + v_{ik}(t+1) \quad \text{(twenty two)}$$

where ω is the inertia weight; c_1, c_2 are two learning factors; $rand1(0,1)$ and $rand2(0,1)$ are two random numbers evenly distributed between (0,1); $i = 1,2,\cdots m$; $k = 1,2\cdots,d$. In addition, the speed of the particle in each dimension V_i is limited by a maximum speed V_{max}. If the current acceleration of the particle causes its speed in a certain dimension to exceed the maximum speed V_{max}, the speed in that dimension is limited to the maximum speed. The third part of equation (21) indicates that particles will communicate with each other.

5. Result Analysis

In this section, we present simulation results and evaluate the performance of our proposed distributed algorithm and solution using particle swarm optimization. In the simulation model, we assume an $N = 10$ energy user. The entire cycle is divided into 24 equal parts, representing one rotation of the earth. The minimum and maximum power requirements of all users are different in each time slot, ensuring the minimum power generation that meets the minimum power requirements. However, we also assume that the maximum generation L_k^{max} equals the maximum total power demand of all users, so we have $L_k^{max} = \sum_{\in N} M_i^k$, for all $k \in K$.

We also assume that the parameters of each user ω are randomly selected from the interval [1, 4] and remain fixed throughout the period. The parameter of the utility function introduced in α equation (8) has a value of 0.5. We set the parameter of the cost function introduced in (12) $a_k = 0.01$ to, $b_k = 0$. $c_k = 0$

The simulation results of total power consumption solved by distributed algorithm and particle swarm algorithm are shown in Figures 2 and 3. Due to the real-time interaction between users and energy suppliers, the total electricity consumption corresponding to the two curves matches the expected power generation capacity of users and energy suppliers. High utilization of available resources while keeping the total power consumption below the required threshold is one of the advantages of the proposed algorithm. As expected, both generation and total power consumption are within the minimum and maximum total power requirements of all users within each time slot.

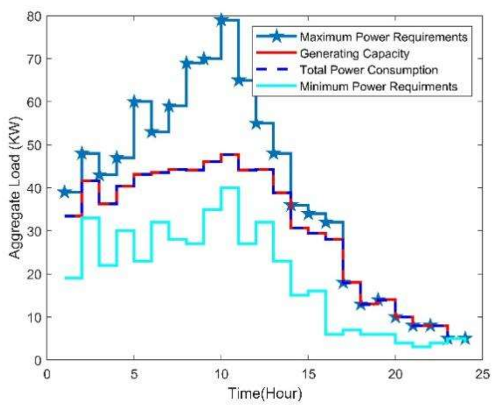

Figure 2. Total power consumption calculated by distributed algorithm

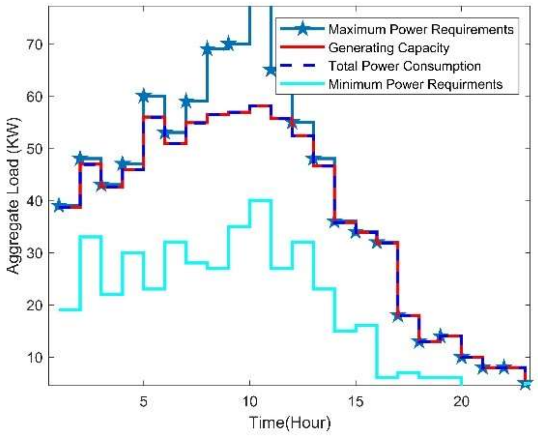

Figure 3. Total power consumption calculated by particle swarm algorithm

For comparison with the proposed real-time pricing strategy, we also consider a fixed pricing scheme with hard constraints to keep total consumption below generation without user interaction. In a fixed pricing algorithm, the energy supplier announces $k \in K$ the price for each time slot at the beginning of the time slot to ensure that ω the total consumption level does not exceed the generation capacity for any type of user with different choices of parameters. Therefore, in the fixed pricing algorithm, ω the worst case scenario in which the parameters of all users takes the maximum value is considered. $\omega_{\max} = 4$ Therefore, $k \in K$ the price per time slot can be calculated as:

$$P_{fixed}^{k} = \omega_{\max} - \frac{L^{k}\alpha}{N} \tag{21}$$

Using distributed algorithm and particle swarm algorithm to solve, the simulation results of the total utility of all users for the two different methods are shown in Figures 4 and 5. We can see that the total utility of our proposed distributed real-time pricing algorithm is much higher than that of the fixed pricing algorithm.

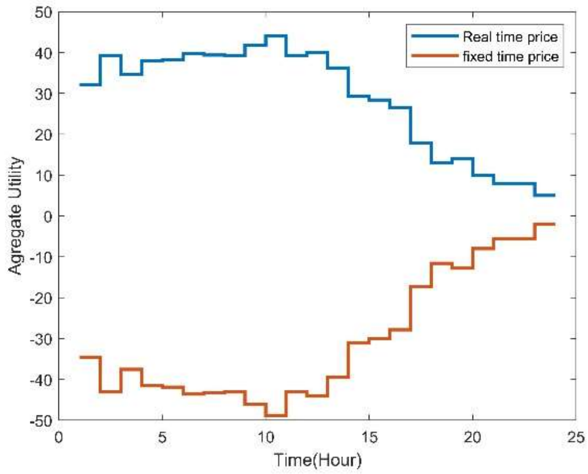

Figure 4. Total consumed power particles swarm optimization is used

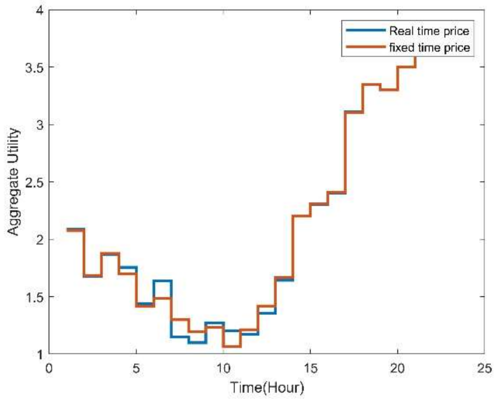

Figure 5. Total consumed power particles swarm optimization is used

6. Conclusion

In this paper, an optimal real-time pricing algorithm for DSM in future smart grids is proposed. The proposed algorithm is based on utility maximization, which can be implemented in a distributed manner to maximize the total utility for users and minimize the loss cost for suppliers while keeping total power consumption lower than generation. In addition, the P SO algorithm is also used for solution. Simulation results confirm that by using our proposed optimization-based real-time pricing model, not only energy providers but also users will benefit.

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