International Journal of Smart Home
Vol. 10, No. 11, (2016), pp. 79-94
http://dx.doi.org/10.14257/ijsh.2016.10.11.08

Price Learning Based Load Distribution Strategies for Demand Response Management in Smart Grid

Qiang Tang[1,2], Ming-zhong Xie[1,2],Kun Yang[3], Yuan-sheng Luo[1,2] and Ping Li[1,2]

[1]Hunan Provincial Key Laboratory of Intelligent Processing of Big Data on Transportation, Changsha University of Science and Technology, Changsha 410114, Hunan Province, China

[2]School of Computer and Communication Engineering Changsha University of Science and Technology, Changsha, China

[3]School of Computer Science and Electronic Engineering University of Essex, Colchester, United Kingdom

[1,2]tangqiangcsust@163.com,[1,2]xiemingzhongcsust@163.com, [3]kunyang@essex.ac.uk

Abstract

In this paper, a Price learning based Load Distribution Strategy (PLDS) is proposed at first. In PLDS model, Smart Power Service, Utility Company and History Load Curves are included, and by considering both the average electricity consumption cost and the average electricity consumption habit, we proposed a convex optimization model to solve the model. In order to accelerate the convergence of PLDS, a price learning mechanism is proposed, which learns a price curve according to the history price data, and predicts price as a learned price for the next iteration. The optimization cycle of PLDS is one day or 24 hours, and in order to further improve the peak shaving performance, an extended version of PLDS named PLRS (Price learning based Load Redistribution Strategy) is proposed, whose optimization cycle length is 1 hour. The optimization models of PLDS and PLRS are the same, and the differences between them are the optimization cycle and the constraint conditions. In the simulation, we compared the convergence performance, peaking shaving performance and total cost among PLDS, PLRS and other strategy ODC in reference [11], and we found that the convergence performances of PLDS and PLRS are both better than that of ODC. The peak shaving performance of PLRS is better than that of ODC in the long term, and the total cost of PLRS is very close to that of ODC.

Keywords: *Price learning, Electricity Consumption Habit, Load Distribution Strategy, Convex Optimization Model*

1. Introduction

In smart grid, Demand Response Management (DRM) plays an important role for both the utility companies and electricity users. For the utility companies, DRM reduces the power at the peak hour, and increases the power at the valley hour in general, which ensures small fluctuations for the generation capacity. For the customers (electricity users), generally DRM increases the electricity price at the peak hour and reduces the electricity price at the valley hour, which shifts the elastic load from the peak hour to the valley hour, which results into the cost reduction.

The DRM mainly has two types: Incentive Based Programs (IBP) and Price Based Programs (PBP) [1-2]. In IBP, the capacity and load are managed by the utility companies, which will increase the capacity or reduce the load actively to balance the capacity and load. Besides, the load demands or capacities can be sold on the market, and the utility companies buy the demand load or capacities for its co-ordination of supply and demand.

ISSN: 1975-4094 IJSH

Although IBP performs well in coordinating the demand and supply, it rarely considers the electricity users' benefits, which are an important consideration in the PBP.

In PBP, the electricity price is not fixed all the time, and by adjusting price the electricity users are guided to use high-power equipment at the low price periods, and consume less electricity at the high price periods. The electricity users can save a lot of cost when the electricity price is varying. The main programs are [3]: Time of Use (TOU), Critical Peak Pricing (CPP), Extreme Day CPP (ED-CPP), Extreme Day Pricing (EDP) and Real Time Pricing (RTP), *etc.* Recent years, many research works have used the dynamic pricing mechanism as an effective way to schedule the demand load. The electricity price is the tie that links the utility company and electricity users. In general, every DRM program has two participation sides, and each participation side has its own utility function and cost function, based on which the DRM program model is built. The objective functions are various.

I. Koutsopoulos *et. al.,* in [4] have proposed a stochastic model and two online demand scheduling programs for the minimizing the long-term average power grid operational cost. The two programs are Threshold Postponement (TP) and Controlled Release (CR), and a queue model is adopted. The two programs can save the operational cost effectively, but the cost of electricity users is not considered. In [5], L. Zheng *et. al.,* proposed a DRM program for the HVAC (heating ventilation and air-conditioning) loads scheduling. The control objective is to reduce the variation of nonrenewable power demand. Based on an extended Lyapunov optimization approach, a control algorithm is proposed to approximately solve the DRM model. In [6], A.-H.Mohsenian-Rad *et. al.,* proposed a game theory based energy consumption scheduling strategy. The global optimal performance in terms of minimizing the energy costs is achieved at the Nash equilibrium of the formulated energy consumption scheduling game. The simulation results showed that the approach can reduce the peak-to-average ratio of the total energy demand, the total energy costs and each user's daily charges. In [7], B. Liu *et. al.,* presented a home energy management scheduling algorithm based on market DR program and household comfort constraints. The comfort constraints are the controlled temperature in the house staying in a suitable range to meet the human body's requirement. This work only considers the TOU pricing, and there is no interaction between the system operator and the electricity users. In [8], P. Yang *et. al.,* propose a game-theoretic approach to optimize TOU pricing strategies (GT-TOU). User demand fluctuations are used to model the utility companies' cost, and the difference between the nominal demand and the actual consumption is modeled as the cost of user. The optimal TOU price is achieved at the Nash equilibrium. The simulation results showed that the method is effective in leveling the user demand, decreasing the costs for the utility companies, and increasing user benefits.

As the electric vehicle (EV) increase, designing a DRM for the EV charging is an important issue. In [9], the authors pointed out that a more dynamic electricity price would allow the users save more money and manage their usage preferences more flexibly. In order to get a real-time pricing program, the authors proposed a differential equation model for the EV charging DRM, and after some iteration the electricity price and the demand converge to a stable optimal value. In [10], Z. Tan *et al.,* proposed a DRM model which contains the renewable distributed generators for the EV charging. In this model, the price contains two parts: the base price which is fixed and the fluctuation cost. The EVs can sell back energy to the grid. Simulation results show that the DRM model has the ability to shift the demand and save money for electricity users. L. Gan *et. al.,* in [11] have proposed a decentralized protocol ODC (Optimal Decentralized Charging) for the negotiating day-ahead EV charging scheduling, where the EVs select their own charging profiles for the following day according to the electricity price. The algorithm can shift the charging load to fill the overnight electricity demand valley. Although the

ODC is the EV charging algorithm, it also can schedule other electrical equipment for the DRM.

Besides the description above, many other factors are also considered in the DRM. In [12-14], the DRM programs schedule all kinds of loads, and they include many kinds of energy, such as wind energy, solar energy, which are uncertain renewable energy resources. In [15-16], J. M. Guerrero et al studied the DRM for the microgrid, which generates the electricity independently by using the distributed generations, and can sell the redundant electricity to the power grid. In [17], C. Gouveia designed the DRM programs which adopted the energy storage system for the load scheduling.

In [18], R. Deng *et. al.*, reviewed the mathematical models and approaches for the DRM. The authors pointed out that the mathematical approaches are mainly convex optimization, game theory, dynamic programming, markov decision process, stochastic programming and particle swarm optimization. They also concluded that the mathematical models mainly contain two types of function: the utility function and the cost function.

In this paper, we mainly focus on the designing a price learning based DRM program for the load distribution. Our program has two versions: the PLDS and PLRS, which have different cycle lengths. The programs consider the user's average electricity consumption habit, and their convergences are improved after adopting the price learning mechanism. Our contributions lie in accelerating the convergence by designing a price learning mechanism, and proposing two DRM programs PLDS and PLRS with different cycle lengths, and the peak shaving performance as well as total cost of PLRS is similar to that of ODC.

This paper is organized as follows. In Section 2, we introduce the system model and the principles of PLDS. In Section 3, we further introduce the extended version PLRS. In Section 4, we present the simulation results, conclusion and the future work.

2. Load Distribution Strategy PLDS

2.1. Model Definition

In order to introduce the PLDS more clearly, some mathematical variables are defined at first. Let N denote the number of electricity users in the residential area. $P=\{p_1,p_2,p_3,\cdots,p_{24}\}$ is a vector containing the 24 hours calculated prices by the utility company. $X=\{x_1,x_2,x_3,\cdots,x_{24}\}$ is a vector containing the 24 hours average electricity consumption demands for each user in this residential area, and the total demand vector for the 24 hours is $X_t=NX$. $B=\{b_1,b_2,b_3,\cdots,b_{24}\}$ is a vector containing the 24 hours user's average electricity consumption habit, which is also named average basic load. The total electricity consumption habit is $B_t=NB$. Assume every user's house has a smart meter with the same maximum power constraint, which is denoted by Z . We let $Z=\{z_1,z_2,z_3,\cdots,z_{24}\}$, and $z_1=z_2=z_3=\cdots=z_{24}=z$, then every element in X should be less than z .

We assume there are only one utility company and one residential area. In this model, an intermediate organization Smart Power Service (SPS) between the utility company and the residential area electricity users is put forward. The SPS is responsible for the coordination between the utility company and residential users to optimize the electricity price and demand. The frame diagram of PLDS is shown in Figure 1.

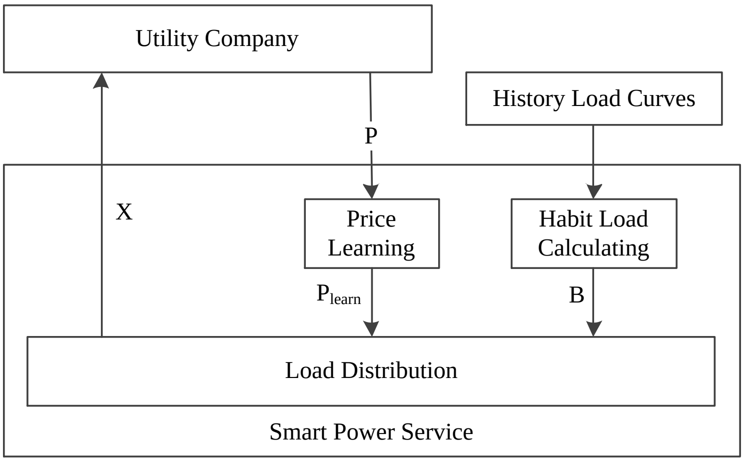


Figure 1. The PLDS Frame Diagram

In PLDS, we schedule the demand in a day, which is the cycle length and divided into 24 hours. In everyday, utility company updates the electricity price according to the average electricity consumption demand X . The SPS updates the average electricity consumption demand X according to the updated price P sent from the utility company. The progress is executed in iterative manner, and in order to accelerate the convergence, a price learning mechanism is proposed. After some iteration, the average electricity consumption demand X and the price P are stable, which means the optimization process is ended. The optimized X and P will be broadcasted to the residential users by SPS, who will make all the residential users obey the optimized average electricity consumption demand through a mechanism, which does not belong to the scope of this paper, and we assume all the users obey the optimized average electricity consumption demand.

The PLDS is executed by SPS, and it contains Load Distribution Module, Price Learning Module and Habit Load Calculating Module. The Load Distribution Module is the core module and in charge of calculating out the optimized X for every electricity users. The Price Learning Module is designed for predicting an electricity price to improve the convergence, and the predicted electricity price is used by the Load Distribution Module. The Habit Load Calculating Module is in charge of calculating out the average electricity consumption habit or average basic load in this area. The average basic load reflects the average electricity usage habit of this residential area.

2.2. Load Distribution Module

In this module, we consider both the average electricity consumption cost and the average electricity consumption habit. The average electricity consumption habit is considered by using the mean square deviation between X and B, which measures the difference between the optimized average electricity consumption demand and the average electricity consumption habit. The optimization problem is:

$$\begin{aligned} &\min PX^T + c\,\| X - B \|_2^2 \\ &s.t.\quad 0 \le x_i \le z, i \in [1,\cdots,24] \\ &\qquad\quad \| X \|_1 = \| B \|_1 \end{aligned} \tag{1}$$

Where the parameter c is adjustable, which belongs to $(0,+\infty)$. If $c = 0$, the problem is a cost minimization problem, and if c is big enough, the problem becomes a difference between X and B minimization problem. The constraint condition $\| X \|_1 = \| B \|_1$ means the sum of the optimized average electricity consumption demand should equals to that of the average electricity consumption habit, in other words, there is no demand reduction, and only demand shift exists in PLDS.

The problem (1) is a convex problem, and it can be transformed into:

$$\begin{aligned} & \min PX^T + c(X-B)\cdot(X-B)^T \\ & s.t. \quad 0 \le x_i \le z, i \in [1,\cdots,24] \\ & \qquad \| X \|_1 = \| B \|_1 \end{aligned} \tag{2}$$

By derivation, we obtain the first order derivative:

$$\frac{df(X)}{dX} = P + 2c(X-B) \tag{3}$$

The optimal value of X without constraint condition is denoted by X_{opt}:

$$X_{opt} = B - \frac{1}{2c}P \tag{4}$$

If we consider the constraint condition for the optimal value of X, (1) should be transformed into a Lagrange function:

$$\begin{aligned} L(x,\mu_1,\mu_2,\mu_3) = & PX^T + c(X-B)\cdot(X-B)^T - \mu_1\cdot(X-Z) \\ & + \mu_2\cdot X + \mu_3\cdot(\| X \|_1 - \| B \|_1) \end{aligned} \tag{5}$$

Where μ_1,μ_2,μ_3 are the Lagrange multipliers. μ_1 and μ_2 are non-negative vector, and μ_3 is a scalar.

Because the vector X and B are both non-negative, the constraint condition $\|X\|_1 = \|B\|_1$ is converted into:

$$(X-B)\cdot I^T = 0 \tag{6}$$

Where $I = \{1,1,1,\cdots,1\}$ is a unit vector with the size as 24. By replacing (5) with (6), we get:

$$\begin{aligned} L(x,\mu_1,\mu_2,\mu_3) = & PX^T + c(X-B)\cdot(X-B)^T - \mu_1\cdot(X-Z) \\ & + \mu_2\cdot X + \mu_3\cdot(X-B)\cdot I^T \end{aligned} \tag{7}$$

Then we obtain the first order deviation of (7), and the optimized X with the constraint condition:

$$\frac{\partial L(x,\mu_1,\mu_2,\mu_3)}{\partial X} = P + 2c(X-B) - \mu_1 + \mu_2 + \mu_3 I = 0 \tag{8}$$

Because the problem (2) is convex, and there is only one global optimization point X_{opt}. In order to make the optimized X meet the constraint conditions, we construct the Lagrange Function (7) and get the optimized value X_{opt}^c. The optimized X_{opt}^c is located at the neighborhood of X_{opt}. In this paper, we use an iterative manner to search a feasible solution X_{opt}^c which is closest to X_{opt}. The steps are shown in follows:

Step1: initialize $X = X_{opt}$; Set the step size $\lambda_1, \lambda_2, \lambda_3$ and the precision σ.

Step2: calculate the Lagrange multipliers μ_1,μ_2 and μ_3 according to:

$\mu_1 = \lambda_1 \max\{X - Z, 0\}$;

$\mu_2 = \lambda_2 \max\{-X, 0\}$;

$\mu_3 = \lambda_3 (X - B) I^T$.

Step3: update $X^{\{new\}} = X + \frac{1}{2c}(\mu_1 - \mu_2 - \mu_3 I)$.

Step4: If $\| X^{\{new\}} - X \| \le \sigma$, the optimized average demand is obtained and the optimization is ended; else $X = X^{\{new\}}$ and go to **Step2**.

In order to get the optimal value X, we also need the price P and average basic load B, which is acquired from the Price Learning Module and Habit Load Calculating Module respectively.

2.3. Habit Load Calculating Module

In order to get the average electricity consumption habit in this residential area, we use the latest H days' average total load demand curves of this residential area. After being divided by the electricity user number N, we further obtain the average single user's load demand curve in this residential area of the latest H days. We formulate the following equation to calculate the average electricity consumption habit or the average basic load B for each electricity user:

$$\underset{B}{\operatorname{argmin}} f(B) = \sum_{j=1}^{H} (B - X^{\{j\}}) \cdot (B - X^{\{j\}})^T \tag{9}$$

Equation (9) can be solved by setting the first order derivative as zero, and we get the average basic load as:

$$B = \frac{\sum_{j=1}^{H} X^{\{j\}}}{H} \tag{10}$$

2.4. Price Learning Module

In order to accelerate the convergence, we use a learned price as a signal to schedule the average electricity consumption demand X. The price learning module always receives the electricity price from the utility company, and puts it into a training set with the size as M. According to the (11), a price prediction function $P(l)$ is put forward by the Least Square method:

$$\underset{P(l)}{\operatorname{argmin}} \sum_{l=1}^{M} (P(l) - P^{\{l\}}) \cdot (P(l) - P^{\{l\}})^T \tag{11}$$

If we put $M+1$ into $P(l)$, then we can get the predicted price: $P_{learn} = P(l+1)$. When P_{learn} and B are all calculated out, the SPS lets $P = P_{learn}$, and put P and B into (8) to adjust the vector X. The updated X will be sent to the utility company for the price updating. If the utility company has updated a new price according to X, the new price will be sent to the price learning module as a training sample data and then get a newly learned price P_{learn}. The process is repeated until P and X are stable.

3. Extended Load Distribution Strategy PLRS

In the model PLDS, the price P and average electricity consumption demand X are optimized at the beginning of a day, and there is no optimization process executed in other time period of this cycle. In order to make the cycle length more flexible, we propose an extended load distribution strategy PLRS, which optimizes the electricity price and average electricity consumption demand in every hour.

Assume the current time is the k^{th} hour. Let $X_{R1}=\{x_i \mid i\in[1,2,\cdots,k-1]\}$, and $X_{R2}=\{x_i \mid i\in[k,k+1,\cdots,24]\}$, then $X_R=X_{R1}\cup X_{R2}$. The X_{R1} is the optimized and fixed average electricity consumption demand vector for the past k hours and X_{R2} is the not optimized average electricity consumption demand vector for the future 24-k hours. The similar definition is also suitable for the electricity price. Let $P_{R1}=\{p_i \mid i\in[1,2,\cdots,k-1]\}$, and $P_{R2}=\{p_i \mid i\in[k,k+1,\cdots,24]\}$, then $P_R=P_{R1}\cup P_{R2}$.

In the PLRS model, we define a varied average electricity consumption habit $S=X_{R1}\cup S_2$, and $S_2=\{s_j \mid j\in[k,k+1,\cdots,24]\}$. S can be optimized by the following optimization problem:

$$\begin{aligned} &\min \| S-B \|_2^2 \\ s.t.\ & s_i = x_i, 1<i\le k-1 \\ &\|S\|_1=\|B\|_1 \end{aligned} \tag{12}$$

By solving (12), we obtain the optimized vector $S_2^*=\{s_j^* \mid j\in[k,k+1,\cdots,24]\}$. Then we get three vectors with the same size $24-k+1$:

$$S_2^*=\{s_j^* \mid j\in[k,k+1,\cdots,24]\}$$

$$X_{R2}=\{x_j \mid j\in[k,k+1,\cdots,24]\}$$

$$P_{R2}=\{p_j \mid j\in[k,k+1,\cdots,24]\}$$

If we let $B=S_2^*$, $X=X_{R2}^*$, $P=P_{R2}^*$, $Z=\{z_j \mid j\in[k,k+1,\cdots,24]\}$ and put them into (1), *e.g.*, calling PLDS, after a few iterations, we can get the optimized X_{R2}^* and P_{R2}^* respectively:

$$X_{R2}^*=\{x_j^* \mid j\in[k,k+1,\cdots,24]\}$$

$$P_{R2}^*=\{p_j^* \mid j\in[k,k+1,\cdots,24]\}$$

Then we get the optimized average electricity consumption demand x_k^* and price p_k^* at the k^{th} hour, and put them into the optimized vector X_{R1} and P_{R1} respectively:

$$X_{R1}=\{x_i \mid i\in[1,2,\cdots,k-1]\}$$

$$P_{R1}=\{p_i \mid i\in[1,2,\cdots,k-1]\}$$

Where x_k in X_{R1} equals to x_k^* in X_{R2}, and p_k in P_{R1} equals to p_k^* in P_{R2}. Meanwhile, the vector X_{R2}, P_{R2} and S_2 also changed:

$$S_2=\{s_j \mid j\in[k+1,k+2,\cdots,24]\}$$

$$X_{R2}=\{x_j \mid j\in[k+1,k+2,\cdots,24]\}$$

$$P_{R2}=\{p_j \mid j\in[k+1,k+2,\cdots,24]\}$$

The process is repeated in every hour until one day is ended, and finally we obtain the optimized average electricity consumption demand vector $X_{R1} = \{x_i \mid i \in [1,2,\cdots,24\}$ as well as the optimized price $P_{R1} = \{p_i \mid i \in [1,2,\cdots,24\}$. The average electricity consumption cost is $P_{R1} \cdot X_{R1}^T$.

4. Simulation

4.1. Data and Parameters Setting

We chose the PJM market data from March 16 to 20 in 2015, which are statistics hourly load demand and can be acquired from [19]. We assume there are $N = 10000$ users in this residential area. After the PJM market data of these days are divided by N, the average electricity consumption data of these days belong to the interval [2.5kW, 3.3kW] for each user, which is roughly reasonable compared with that in real world. According to the average electricity consumption data of these H=5 days for each user, we calculate the average electricity consumption habit B according to (10). We set $z = 10$ for simplicity.

The price function is $P(x) = 0.043x^{1.3}$, where x is the element of the optimized average electricity consumption demand X for each user. All the related parameters' values are listed in the Table 1:

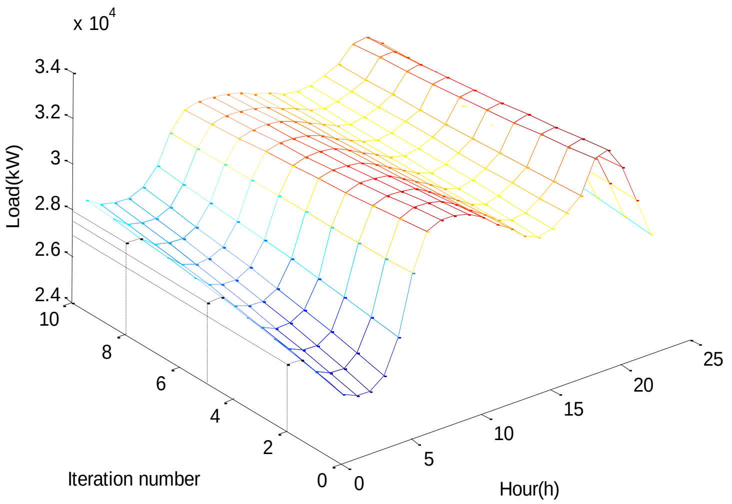
Table 1. Parameters Settings

Name	λ_1	λ_2	λ_3	σ	N	H
Value	-0.01	-0.01	1/24	0.001	10000	5

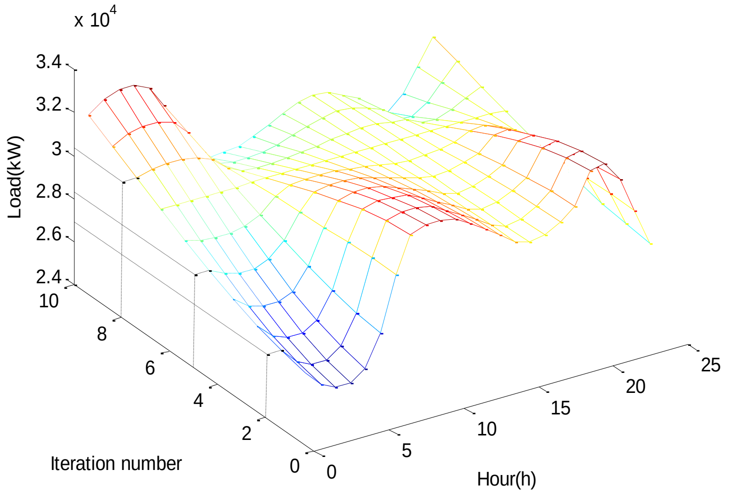
In the following subsections, we simulate the convergence performance of PLDS, and we compare the convergence of PLDS with that of ODC in [11]. We will further simulate the peak shaving performance of PLDS, PLRS and ODC. At last, the electricity consumption costs of these strategies are given.

4.2. Convergence Performance

In order to evaluate the convergence, we compare the PLDS with the ODC in [11]. Because the PLRS calls the PLDS in every hour, the convergence of PLDS is suitable for PLRS, and there is no need to evaluate PLRS's convergence. We set the parameter $c = 1$. The total electricity consumption demand is NX. The convergence performance simulation results are shown in Figure 2.



(a) The demand convergence performance of ODC

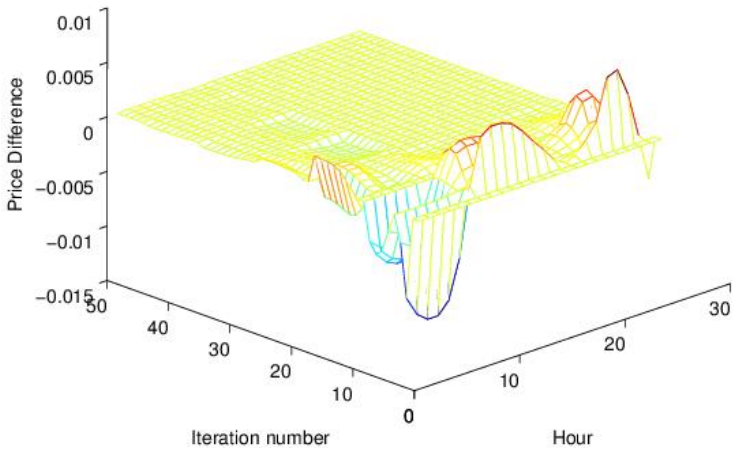


(b) The demand convergence performance of PLDS

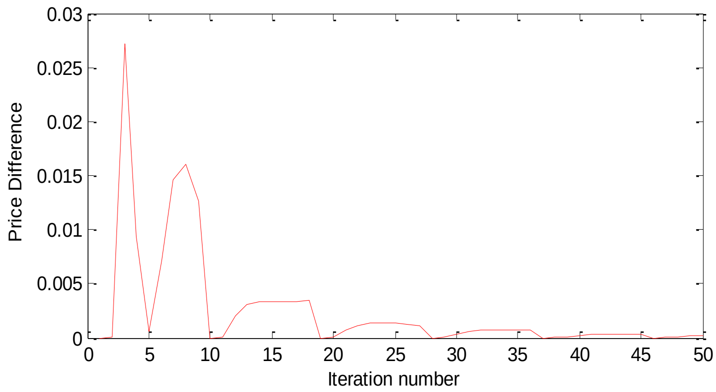
Figure 2. The Total Electricity Consumption Demand Convergence

From the Figure 2, we find that the PLDS converges to a demand curve with small peak load, and the peak-valley difference is decreased rapidly. We also find that the ODC's convergence performance is worse than that of PLDS, and the total electricity consumption demand curve of PLDS is more flat than that of ODC when the iteration number is 7.

As the simulation iteration increases, the learned price also converges to the price calculated by the utility company, which is shown in Figure 3. We let $P_{learn} - P$ denote the difference between the learned price and the real price (calculated by utility company in each iteration), and let the Euclidean distance measure the difference between them.



(a) The price convergence



(b) The Euclidean distance converges to zero

Figure 3. The Convergence Performance of Price

In Figure 3(a), the difference between the learned price and the real price gradually converges to a Zero vector. In Figure 3(b), the distance of the two prices gradually converges to zero, which means that after some iteration, the learned price equals to the real price.

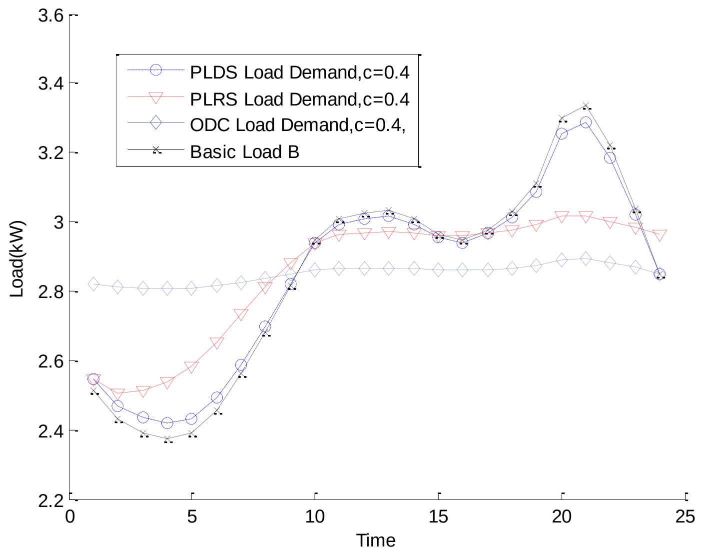
4.3. Peak Shaving Performance

In this subsection, we will simulate the total optimized electricity consumption demand curve to illustrate the peak shaving efficiency of PLDS, PLRS and ODC. The parameter c is set as 0.4. In order to describe the peak shaving performance better, we set three circumstances, which have different cycle length and starting point. The circumstances parameters are set in Table 2.

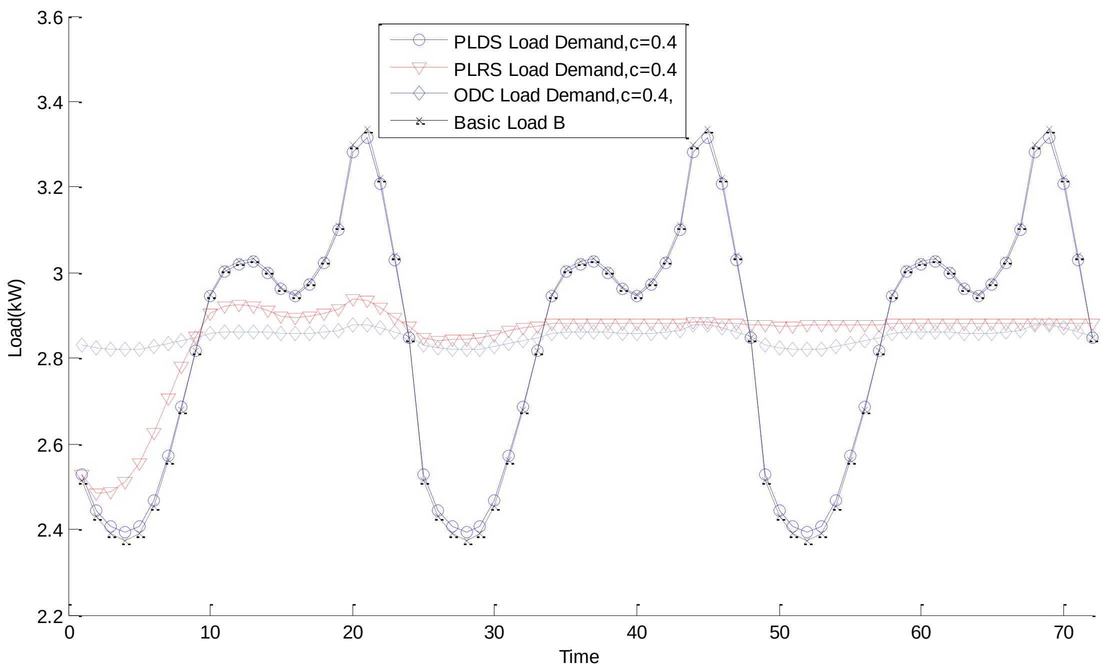
Table 2. Circumstances Parameters Settings

Para. Name	*Cycle Length*	*Starting Point*	*Ending Point*
Circumstances One	24 hours	1:00 AM	12:00 PM next day
Circumstances Two	72 hours	1:00 AM	12:00 PM after three days
Circumstances Three	72 hours	8:00 AM	8:00 AM after three days

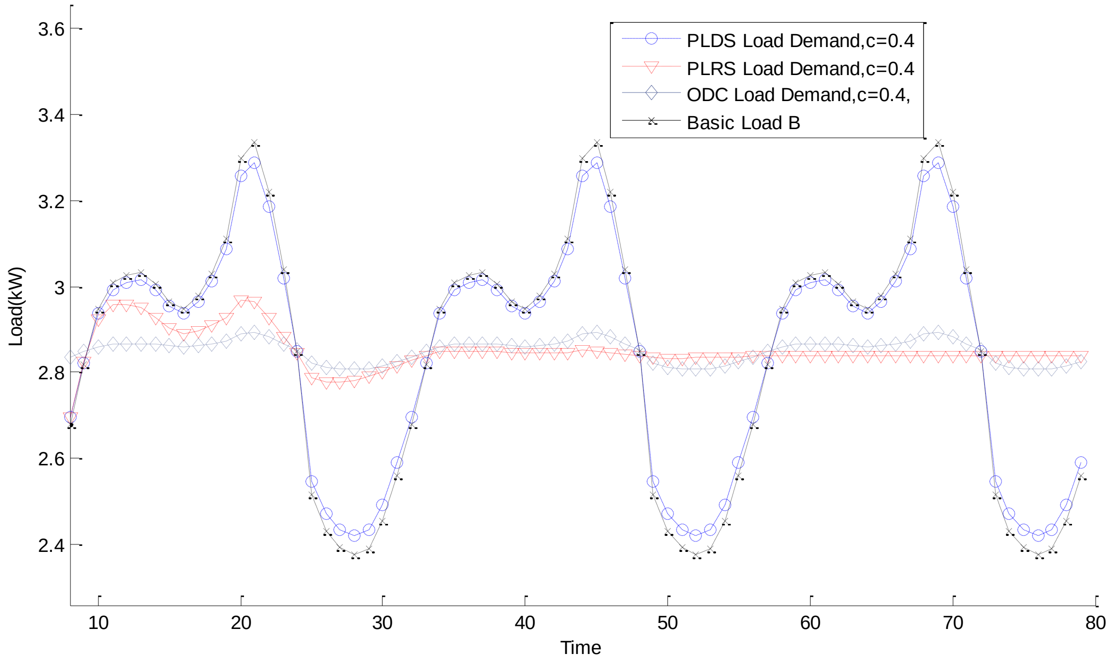
In Circumstances One, the PLDS only executes the optimization strategy at the 1:00 AM, and calculates out the following 24 hours optimization demand vector X. In the Circumstances Two and Circumstances Three, the PLDS also only executes the optimization strategy at the first time period. The PLRS will execute the optimization strategy at every hour in all the circumstances. The total electricity consumption demand curves are shown in the Figure 4.



(a) The total electricity consumption demand curves in Circumstances One



(b) The total electricity consumption demand curves in Circumstances Two



(c) The total electricity consumption demand curves in Circumstances Three

Figure 4. The Total Electricity Consumption Demand Curves

In Figure 4(a), we find that the optimized total electricity consumption demand curve of PLRS has better performance in peak shaving compared with PLDS. But both PLDS and PLRS have poor performance compared with ODC, and we think the main reason for this phenomenon is that PLDS only executes once at the starting point of the cycle, and PLRS executes at each hour to adjust the optimization demand for the future hours. Because PLRS calls PLDS at each hour, the peak shaving performance will be similar with that of PLDS in the first few hours.

As time goes on, we find that PLRS has the smaller load fluctuations compared with that of ODC, which illustrates that PLRS has better peak shaving performance in the long term shown in Figure 4(b), and Figure 4(c).

Because PLDS only executes the optimization process only once, its peak shaving performance is the worst among these three strategies.

4.4. Electricity Consumption Cost

In order to evaluate the total electricity consumption costs of PLDS, PLRS, and ODC we compare them with the strategy Without Load Distribution (WLD). The total electricity consumption cost of WLD is calculated as $N\sum_{i=1}^{24} P(b_i)b_i$, and that of PLDS and PLRS are NPX^T and $NP_{R1}X_{R1}{}^T$ respectively.

In order to evaluate the electricity consumption cost, we select a cycle which starts from the 8:00 AM and ends at 8:00 AM in the next day. The simulation parameters are the same with that in subsection 4.3. Simulation results are shown in the Figure 5.

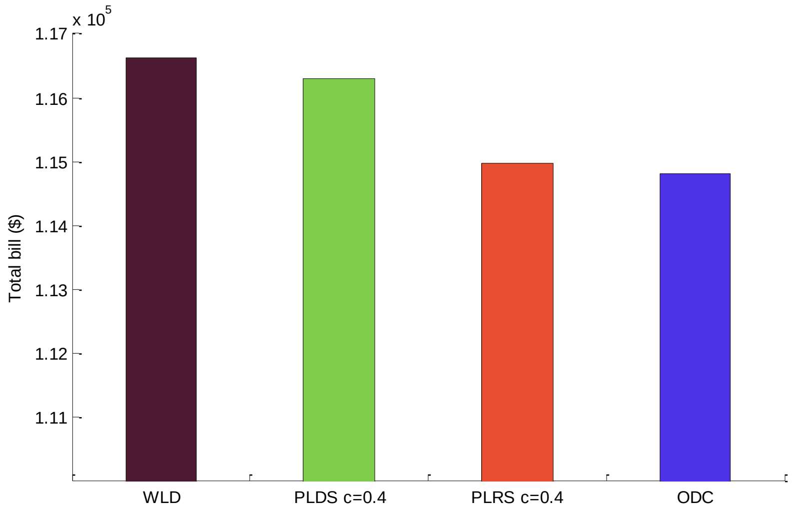


Figure 5. The Total Electricity Consumption Cost

According to Figure 5, we find that the total cost of ODC is the minimum, and the total cost of PLRS is very close to that of ODC. The reason for this result is that the cycle length is 24 hours, which is too short for PLRS, and the peaking shaving of PLRS is worse than that of ODC. The PLDS has the highest total cost among these three strategies PLDS, PLRS and ODC. The WLD has the worst cost saving performance.

5. Conclusion and Future Work

In this paper, we propose a price learning based load distribution strategy PLDS and an extended strategy PLRS. In PLDS, the cycle length is 24 hours, and that of PLRS is 1 hour. The PLDS executes the optimization process only once at the starting point of the cycle, and PLRS executes the optimization process at each hour of the cycle. The PLRS calls the PLDS at each hour. Simulation results show that the PLDS has better convergence compared to ODC. PLRS has a better peak shaving compared to that of ODC in the long term. In terms of the total cost, the cost of PLRS is very close to that of ODC.

Although the SPS has optimized the average electricity consumption demand, users may not be so consistent in real life. Then how to design a mechanism making all the users obey the optimized average electricity consumption demand in maximum degree is our future work.

Acknowledgments

The work presented in this paper was in part funded by Projects Supported by Scientific Research Fund of Hunan Provincial Education Department (No.13C1022, 13C1023 ,14A004), and a Project supported by the Natural Science Foundation of Hunan Province, China (Grant No. 13JJ4052). It is also partly funded by a Project supported by the National Natural Science Foundation of China (Grant No. 61303043).

References

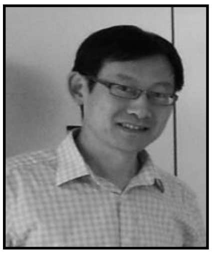
[1] M. H. Albadi and E. F. El-Saadany, "Demand Response in Electricity Markets: An Overview", Proceedings of the IEEE Power Engineering Society General Meeting, Tampa, FL, **(2007)** June 24-28.
[2] P. Siano, "Demand Response and Smart Grids-A survey", Renewable and Sustainable Energy Reviews, vol. 30, no. 2, **(2014)**, pp. 461-478.
[3] J. S. Vardakas, N. Zorba and C. V. Verikoukis, "A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms", IEEE Communications Surveys & Tutorials, vol. 17, no. 1, **(2015)**, pp. 152-178.

[4] I. Koutsopoulos and L. Tassiulas,"Optimal control policies for power demand scheduling in the smart grid", IEEE Journal on Selected Areas in Communications, vol. 30, no. 6, **(2012)**, pp. 1049-1060.
[5] L. Zheng and L. Cai, "A Distributed Demand Response Control Strategy Using Lyapunov Optimization", IEEE Transactions on Smart Grid, vol. 5, no. 4, **(2014)**, pp. 2075-2083.
[6] A. H. Mohsenian-Rad, V. Wong, J. Jatskevich, R. Schober and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid", IEEE Transactions on Smart Grid, vol. 1, no. 3, **(2010)**, pp. 320-331.
[7] B. Liu and Q. Wei, "Home energy control algorithm research based on demand response programs and user comfort", Proceedings of the International Conference on Measurement, Information and Control (ICMIC), Harbin, China, **(2013)** August 16-18.
[8] P. Yang, G. Tang and A. Nehorai, "A game-theoretic approach for optimal time-of-use electricity pricing", IEEE Transactions on Power System, vol. 28, no. 2, **(2013)**, pp. 884-892.
[9] Z. Fan, "A Distributed Demand Response Algorithm and Its Application to PHEV Charging in Smart Grids", IEEE Transactions on Smart Grid, vol. 3, no. 3, **(2012)**, pp. 1280-1290.
[10] Z. Tan, P. Yang and N. A, "An Optimal and Distributed Demand Response Strategy with Electric Vehicles in the Smart Grid", IEEE Transactions on Smart Grid, vol. 5, no. 2, **(2014)**, pp. 861-869.
[11] L. Gan, U. Topcu and S. Low, "Optimal decentralized protocol for electric vehicle charging", IEEE Transactions on Power System, vol. 28, no. 2, **(2013)**, pp. 940-951.
[12] L. Jiang and S. Low, "Multi-period optimal energy procurement and demand response in smart grid with uncertain supply," Proceedings of the 50th IEEE Conference on Decision and Control and European Control Conference. (CDC-ECC), Orlando, FL, **(2011)** December 12-15.
[13] L. Jiang and S. Low, "Real-time demand response with uncertain renewable energy in smart grid," Proceedings of the IEEE 49th Allerton Conference on Communication, Control and Computing, Monticello, IL, **(2011)** September 28-30.
[14] M. He, S. Murugesan and J. Zhang, "Multiple timescale dispatch and scheduling for stochastic reliability in smart grids with wind generation integration," Proceedings of the IEEE INFOCOM, Shanghai, China, **(2011)** April 10-15.
[15] J. M. Guerrero, P. C. Loh, M. Chandorkar and T.-L. Lee, "Advanced control architectures for intelligent microgrids—part I: Decentralized and hierarchical control," IEEE Transactions on Industrial Electronics, vol. 60, no. 4, **(2013)**, pp. 1254–1262.
[16] J. M. Guerrero, P. C. Loh, T.-L. Lee and M. Chandorkar, "Advanced control architectures for intelligent microgrids—part II: Power quality, energy storage, and ac/dc microgrids," IEEE Transactions on Industrial Electronics, vol. 60, no. 4, **(2013)**, pp. 1263–1270.
[17] C. Gouveia, J. Moreira, C. L. Moreira and J. A. Pecas Lopes, "Coordinating storage and demand response for microgrid emergency operation," IEEE Transactions on Smart Grid, vol. 4, no. 4, **(2013)**, pp. 1898–1908.
[18] R. Deng, Z. Yang, M. Y. Chow and J. Chen, "A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches", IEEE Transactions on Industrial Informatics, vol. 11, no. 3, **(2015)**, pp. 570-582.
[19] PJM, PJM-Metered Load Data, **(2016)**, http://www.pjm.com/markets-and-operations/ops-analysis/historical-load-data.aspx.

Authors

Qiang Tang, is currently a lecturer at School of Computer and Communication Engineering in Changsha University of Science and Technology, Changsha, China. He received his Ph.D., M.S. and B.E. degrees from Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan, China, in 2010, 2007 and 2005, respectively. His main research interests include: topology control of wireless networks (including ad-hoc networks, sensor networks), smart grid, resource optimization and scheduling theory.

Mingzhong Xie, is currently a postgraduate student at School of Computer and Communication Engineering in Changsha University of Science and Technology, Changsha, China. His research interests are wireless networks and smart grid.



Kun Yang, is a Full Professor in School of Computer Science & Electronic Engineering (CSEE), University of Essex, and the Head of the Network Convergence Laboratory (NCL), University of Essex. He is a Fellow of IET, Senior Member of IEEE, Member of IEEE ComSoc, and Member of ACM. He received his PhD degree in network engineering from the Department of Electronic & Electrical Engineering, University College London (UCL). His MSc and BSc degrees were both from Department of Computer Science, Jilin University (JLU), China. His main research interests include: Wireless networks (including WiMAX, WiFi, mobile ad-hoc networks, sensor networks), heterogeneous wireless networks, network convergence (inc. fixed mobile convergence), IP network management, Future Internet technologies (such as network virtualization and information centric networking), pervasive service engineering, mobile cloud computing.

Yuan-sheng Luo, is currently a lecturer at School of Computer and Communication Engineering in Changsha University of Science and Technology, Changsha, China. He received his Ph.D. degree from the Department of Computer Science and Technology, Xi'an Jiaotong University, in 2010. His M.S. and B.S. degrees were both from the Software School, Hunan University, in 2005 and 2002, respectively.He received the Best Student Paper Award in the International Conference on Service Science (ICSS), in 2009. His current interests are: Service Composition, Wireless Networks.

Ping Li, is currently a professor at School of Computer and Communication Engineering in Changsha University of Science and Technology, Changsha, China. He is an academic leader of Hunan Provincial Key Laboratory of Intelligent Processing of Big Data on Transportation. He got his Ph.D. degree from the Hunan University. His main research interests include: network and information security, internet of things and sensor networks, data mining and big data processing.

