

A New Real-Time Pricing Scheme Considering Smart Building Energy Management System

Mohammad-Hossein Shariatkhah¹, Mahmoud-Reza Haghifam², Mohammad-Kazem Sheikh-El-Eslami³

1.2.3 Tarbiat Modares University, Tehran, Iran. E-mail: m.shariatkhah@modares.ac.ir, haghifam@modares.ac.ir, aleslam@modares.ac.ir

Abstract

Real-time pricing schemes make the customers to feel the energy price volatility and improve their load profiles. However, these schemes have no significant effect on demand-side uncertainty reduction. In this paper, considering smart grid infrastructures and smart building Energy Management System (EMS), a new real-time pricing scheme is presented to reduce the uncertainty of demand-side. In the proposed method, EMS announces its electric demand during each period of next day to the retailer. The price of energy for the pre-specified amounts is day-ahead price, but any deviation from this amount is settled through spot market price will be determined several minutes before the corresponding period by retailer. Numerical results of an illustrative example are implemented to demonstrate how this scheme makes motivation in customers to reduce their demand uncertainties.

Keywords: Real-Time Pricing, Energy Management System (EMS), Uncertainty; Retailer, Customer.

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1. Introduction

In traditional power system, small customers engage in fixed-price contracts with retailers, which do not reflect the volatile price of wholesale electricity market. Moreover, the customer's electricity demand has usually uncertainty. Therefore, during some periods the electricity demand exceeds the amount that the retailer has contracted to buy in day-ahead market and it has to purchase the difference on the spot market at the spot price of that period. To stay in business, a retailer should adjust the constant price for its clients at a level which is high enough to envelope the costs of purchasing energy in wholesale market [1].

Economic theory dictates that efficient pricing is achieved when electricity is priced at the marginal cost of supplying the last increment of electricity demand, and a perfectly competitive market can provide this [2]. Based on this concept, time-varying electricity pricing schemes (e.g. real-time pricing, time-of-use) were presented, in which, the retail electricity price changes frequently that reflects the volatile price of wholesale electricity market [3-5]. In time-of-use pricing, both prices and time periods are known ex ante and are fixed for some duration (e.g., a season). In contrast, in real-time pricing, generally prices change on an hourly basis and are fixed and known only on a day-ahead or hour-ahead basis [6]. It was costly for small consumers to monitor and evaluate the hourly prices and constantly optimize the use of equipments; therefore, the real-time pricing scheme was not attractive for many customers [7]. However, with technology advancements in smart grid environments, it is applicatory to use real-time pricing schemes.

Real-time pricing schemes cause customers to feel the real price of electricity and encourage them to improve their load profile; however, they have not any significant effect on the demand-side uncertainty reduction. In this paper a novel pricing scheme in a smart environment is presented to reduce demandside uncertainties considering Energy Management System (EMS) of smart homes or small business. Numerical results of a simple case study are implemented to show how more customer presence in market and uncertainties reduction leads to energy costs reduction.

2. Smart grids and EMS

In General, when a market is efficient that the costs associated with the trading be a small part of the value of transaction [1]. In traditional systems it was not worthwhile for small customers to employ specialized personnel to forecast their demand and participate in the electricity markets. However, in a smart grid environment communication and information infrastructures and also smart building EMS can be implemented to enable more presence of customers in the market.

In a smart building all devices can be monitored and controlled via the central EMS. The EMS determines appliances and Distributed Energy Resources (DERs) scheduling based on real-time electricity prices during different periods which are announced by external signals and can bring benefits for customers by reduction in their electricity bill and increment in customer comfort [8-9].

To make this optimization, EMS should have the data of electricity real-time prices and building resident behavior in the next day. To access these data EMS implements external signals and the data which it receives from building residents [8-9]. However, a forecasting should be done for impossible data. This forecasting can be done completely by EMS itself or it can use bidirectional communication to take the utility help. Therefore, it can optimize the appliances and Distributed Energy Resources (DERs) scheduling and determine the customer electricity demand during each period of next day. Customers can announce their demand data to retailer and participates in load forecasting process without incurring any considerable additional costs. In this paper this ability of EMSs is used to present a new pricing method.

3. New pricing method

The rising share of DERs in power system has increased uncertainties in the amount of energy generation. Science most of DERs are installed near end-customers, their uncertainty will be taken into account in demand-side uncertainties [3]. Moreover, the amount of energy consumption has always had uncertainty. The demand-side uncertainties can result in imbalances between actual load and scheduled generation which has been determined based on the required demand forecasting by retailers. Therefore, it is needed to provide the difference of energy in a spot market to avert the system collapse, which usually have more cost than supplying energy in a forward or day-ahead market. In addition, always it would be needed to provide an amount of ancillary services, which increase the energy price [1].

As it mentioned before, real time pricing were presented to encourage the customers to improve their load profile and improve market efficiency. The realtime pricing schemes can be classified in two clusters:

In the first one, which is called day-ahead pricing, once a day the customers are informed of the forecasted electricity prices during each time interval of next day [4]. In this scheme, the EMS can optimize the appliances and DERs scheduling for next day based on the announced prices. The challenge is that this scheme does not reflect the spot market prices which are affected by weather conditions, generator failures, scarcity of generation, or other contingencies that may occur in a wholesale electricity market. Therefore, customers may consume more energy in some periods disregarding that the spot market price may be very high.

However, most of the studies have presented the second kind of scheme, spot real-time pricing. In this scheme, the customers receive hourly price information several minutes prior to the corresponding hour [5]. As the EMS has access just to the past and current prices, to optimize the appliances scheduling it is required to forecast the prices for the following 24-t hours [8-9]. The forecasting will have always an error, so the scheduling would not be exactly optimal. On the other hand, it is difficult to model the response of customers (consumer and small supply units) to price varying and therefore, this scheme itself provokes the demand side uncertainties. Consequently, if the reaction of customers demand is in a big scale, the market prices will not be right anymore [3].

As it can be seen, though these real-time pricing schemes make the customer to improve their load profile and increase its load factor, however, it has not any significant effect on its uncertainty improvement and in some cases they may lead to market inefficiencies.

In this paper, implementing the mentioned ability of EMS, a new pricing scheme is presented that makes the customers responsive of their demand uncertainty. The proposed method is a combined of day-ahead and spot real-time pricing. In this method, once a day, the EMS optimizes the appliances and DERs scheduling and then inform the retailer its electricity demand during each periods of next day. The retailer use these demand data to forecast the aggregate amount over all its customers and participates in day-ahead market to buy the demand. Considering the market price, retailer provides a dayahead real-time price list which represents the price in retail level during each hour of next day. In addition, it determines a spot real-time price for each hour, several minutes before the corresponding hour. Consuming electric energy with the amount of requested energy by the EMS during a period is settled with the day-ahead prices, but any deviation from the requested amount during that period will be cleared with the spot real-time price. Note that if a customer consumes less that its requested energy, it should pay the whole cost of requested energy based on day-ahead prices.

Before each period, considering the day-ahead and spot real-time prices, the requested amount for energy and the residents desired increment or decrement from that requested amount, EMS optimize the scheduling of appliances and DERs during that period. If there is more or enough electricity supply in the market, the spot price will be lower or near to the day-ahead price and EMS will be free in increasing the energy demand. However, EMS avoid too deviation from the requested amount when spot price is high. Therefore the demand uncertainties will decrease, especially when there are costly.

In this method customers should pay the cost of participating in spot market, not retailer. Therefore, implementation of this method encourages customers to reduce their uncertainties.

4. Numerical studies and discussion

A retailer with two customers A and B, as shown in Fig.1, is used as a simple test system to demonstrate the impact of customers' uncertainties on the cost and the revenues of a retailer and to show the effectiveness of the proposed method. Some data like day-ahead and spot prices are borrowed from the Example 4.1 of [1].

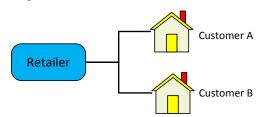


Fig.1. Test system

Four different scenarios have been considered during 12 one-hourly periods as are presented as followings. More details of these scenarios are shown in table of appendix.

Scenario I: In this scenario both customers consume more energy than the forecasted amount; therefore, the retailer <u>participates</u> in spot market to purchase the difference.

Scenario II: In this scenario both customers consume energy exactly equal to their forecasting

load; therefore, it is <u>not necessary</u> for the retailer to participate in the spot market.

Scenario III: In this scenario the uncertainty of customer A is 3 times with respect to customer B; therefore, the retailer <u>participates</u> in spot market to purchase the difference. It is assumed that the demand uncertainty (the difference between the total forecasted demand and the total actual consumed energy) is equal to scenario I.

Scenario IV: in this scenario the uncertainties of customers are equal to each other during all hours and they compensate each other's uncertainty; therefore, it is <u>not necessary</u> for the retailer to participate in the spot market.

In this example, the retailer costs are the costs of participating in wholesale market (both day-ahead and spot market). The retailer revenues and profits depend on retail pricing scheme. The day-ahead and spot prices at retail level have been assumed equal to the wholesale market. For these four scenarios when the pricing scheme is a day-ahead pricing, spot realtime pricing or the presented pricing, the retailer's revenues and profits are calculated. Table.1 shows the results of these scenarios.

Table.1 The numerical results of day-ahead pricing scheme, spot real-time pricing scheme and the proposed pricing scheme

pricing scheme and the proposed pricing scheme										
		Scenario I	Scenario II	Scenario III	Scenario IV					
Customers data	Actual load for customer A	395	5 383 401		377					
	Actual load for customer B	395	383	389	389					
ŭ	Total actual load	790	766	790	766					
	Imbalances	24	0	24	0					
Retailer costs	Day-ahead market costs	28892.2	28892.2	28892.2	28892.2					
teta	Spot market costs	1842.6	0	1842.6	0					
Ľ.	Total costs	30734.8	28892.2	30734.8	28892.2					
p	Customer A payment	14971.8	14446.1	15234.65	14183.25					
day-ahead	Customer B payment	14971.8	14446.1	14708.95	14708.95					
iy-a	Retailer revenues	29943.6	28892.2	29943.6	28892.2					
dî I	Retailer profits	-791.2	0	-791.2	0					
	Customer A payment	22374.6	21453.3	22835.25	20992.65					
spot	Customer B payment	22374.6	21453.3	21913.95	21913.95					
spot	Retailer revenues	44749.2	42906.6	44749.2	42906.6					
	Retailer profits	14014.4	14014.4	14014.4	14014.4					
	Customer A day- ahead cost	14446.1	14446.1	14446.1	14446.1					
The proposed pricing scheme	Customer A spot cost	1027.6	0	1541.4	53.15					
d p	Customer A payment	15473.7	14446.1	15987.5	14499.25					
oposed	Customer B day- ahead cost	14446.1	14446.1	14446.1	14446.1					
pr	Customer B spot cost	1027.6	0	513.8	513.8					
The	Customer B payment	15473.7	14446.1	14959.9	14959.9					
	Retailer revenues	30947.4	28892.2	30947.4	29459.15					
	Retailer profits	212.6	0	212.6	566.95					
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As it can be seen in scenarios I and III, the uncertainties make the retailer to participate in spot market and its total costs have increased 1842.6 \$ with respect to the scenarios II and IV that their total costs are 28892.2 \$. In these scenarios, I and III, the total costs are 30734.8 \$, but if the retailer was able to forecast the actual load correctly and buy the total actual load from day-ahead market, the total cost would become 29943.6 \$.

Results of the retailer profits for the day-ahead pricing scheme, demonstrate that if the retailer adjust the retail level day-ahead prices equal to day-ahead wholesale market, it may lose money when the load has uncertainty and it has to participate in spot market. Moreover, its profit is zero when there is not any uncertainty. Therefore, to cover the risks of participating in spot market and gain profit, retailer should adjust the retail level price more than the wholesale market.

In the spot real-time pricing scheme, the retailer profit is high. That is because it has been assumed that the retailer adjust the retail level prices on spot wholesale market which are high during some periods. It is not suitable that the retailer adjusts the retail level spot prices based on wholesale market price even if it adjusts the prices less than the wholesale prices. That is because the retailer buys most of the energy in day-ahead market, not spot market. The energy price which retailer determines for customers should be an outcome of the average cost of energy, so determining the price based on spot market price may be desultory for some periods. On the other hand, the retailer wants to control its customers' consumption by pricing signals which represent the spot market prices, so pricing based on average energy cost would not satisfy it in getting to its purpose. As it is shown in Table, in this case study when the scheme is spot pricing, the retailers revenue is 14014.4 \$ for all four scenario, which is equal to the difference between the costs that retailer pays for buying the forecasted load in day-ahead market based on day-ahead prices and the money that it gets form customers for that amount of load based on spot prices. The money which retailer pays for participating in spot market will be cleared by customers' payments because there are both based on spot price market.

It can be seen from the retailer profits for the proposed real-time pricing scheme that in this scheme the retailer will not lose money and also its profits will not become irrational high.

Science usually there are some customers that consume more energy than their corresponding forecasted load and some which consume less, they will offset a degree of each other uncertainties. Therefore the retailer will not pay for that amount of uncertainty in spot market but based on the proposed scheme it will get money for those uncertainties from each of customers. This make a source of income for the retailer - as it can be seen from the retailers profit for scenario four- and it help it to adjust the retail price equal or near the wholesale market and cover its miscellaneous expenses and gain profit through these types of income.

In the scenario III the uncertainties of customer A have been assumed 3 times with respect to customer B. In the proposed scheme customer A pays 6.86% more than customer B while in the day-ahead and spot schemes customer A pay 3.57% more than B. It demonstrates that in proposed scheme if the behaviors of some customers make more uncertainty in demand-side, implementing this scheme encourage them to change their behavior. Moreover, in this scheme if a customer have no uncertainty it will not pay for the uncertainties of other customers.

It should be noted that in this case study the dayahead and spot prices have been assumed fixed. However, implementing the proposed scheme for all customers of a system results in reduction of uncertainties, which will reduce the market prices. That is because in short-run it is less needed to provide energy in spot market by the generators that are usually low efficient and expensive, so the spot prices will be set to the marginal cost of more efficient generators. Moreover, in long-run, reduction in uncertainties lead to decreasing the amount of required amount of ancillary services and its corresponding costs e.g. capacity payment.

5. Summery and conclusion

This paper presented a new real-time pricing scheme which attempts to make customers more responsive about their load uncertainties. In proposed method it was considered that a smart building EMS has the ability to forecast the required demand of a building and inform it to the retailer. However, the emphasis of the scheme is not on the forecasting methodology and it is on the implementing the smart grids infrastructures e.g. bidirectional communication and EMS to assign an amount of forecasted load to each customer and settling with customers based on their corresponding forecasted load. The customers should pay energy based on day-ahead prices for their corresponding forecasted load and they should pay the cost of their deviation based on spot real-time prices. The benefits of using this scheme are as follows:

1. It enables the effective presence of customers in load forecasting process which will result in more accurate demand-side forecasting, considering the rising share of DERs near the end-users.

- 2. It make customer responsive to reduce their uncertainties. In turn, it leads to reduction in the cost of the supplied energy.
- 3. As the customers pay the cost of their uncertainty, it is not necessary for retailer to adjust a retail lever price enough high to cover its risks of participating in spot markets.
- 4. This scheme makes new sources of income for the retailer so it can adjust the retail price equal or near the wholesale market and cover its miscellaneous expenses through these types of income.

It is a fair scheme. If a customer has no uncertainty, it will not pay for others uncertainty and if the behavior of a customer makes stress in the power system, it would pay the cost of its uncertainty.

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Appendix

Table.3

The data of four different scenarios during 12 one-hourly periods																
	Period	Units	1	2	3	4	5	6	7	8	9	10	11	12	Total	Average
	Day-ahead prices	(\$/MWh)	24.7	24.5	27.5	35.2	40.7	42.4	45.5	48.6	44.2	38.8	33.4	27.7		36.1
	Spot prices	(\$/MWh)	13.2	12.5	17.4	33.3	69.7	75.4	70.1	102.3	81.4	63.7	46.9	18.3		50.35
	Load forecasted for customer A	(MWh)	22	22	25	32	36	37	39	41	38	34	30	27	383	31.91667
	Load forecasted for customer B	(MWh)	22	22	25	32	36	37	39	41	38	34	30	27	383	31.91667
	Total forecasted load	(MWh)	44	44	50	64	72	74	78	82	76	68	60	54	766	63.83333
Scenario I	Actual load for customer A	(MWh)	20	20	29	33	36	40	41	41	40	38	33	24	395	32.91667
	Actual load for customer B	(MWh)	20	20	29	33	36	40	41	41	40	38	33	24	395	32.91667
	Total actual load	(MWh)	40	40	58	66	72	80	82	82	80	76	66	48	790	65.83333
	Imbalances	(MWh)	-4	-4	8	2	0	6	4	0	4	8	6	-6	24	2
	Actual load for customer A	(MWh)	22	22	25	32	36	37	39	41	38	34	30	27	383	31.91667
io II	Actual load for customer B	(MWh)	22	22	25	32	36	37	39	41	38	34	30	27	383	31.91667
Scenario II	Total actual load	(MWh)	44	44	50	64	72	74	78	82	76	68	60	54	766	63.83333
	Imbalances	(MWh)	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scenario III	Actual load for customer A	(MWh)	19	19	31	33.5	36	41.5	42	41	41	40	34.5	22.5	401	33.41667
	Actual load for customer B	(MWh)	21	21	27	32.5	36	38.5	40	41	39	36	31.5	25.5	389	32.41667
	Total actual load	(MWh)	40	40	58	66	72	80	82	82	80	76	66	48	790	65.83333
	Imbalances	(MWh)	-4	-4	8	2	0	6	4	0	4	8	6	-6	24	2
Scenario IV	Actual load for customer A	(MWh)	23	23	23	31.5	36	35.5	38	41	37	32	28.5	28.5	377	31.41667
	Actual load for customer B	(MWh)	21	21	27	32.5	36	38.5	40	41	39	36	31.5	25.5	389	32.41667
	Total actual load	(MWh)	44	44	50	64	72	74	78	82	76	68	60	54	766	63.83333
	Imbalances	(MWh)	0	0	0	0	0	0	0	0	0	0	0	0	0	0