Energy 46 (2012) 221–230

Contents lists available at SciVerse ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

A day-ahead electricity pricing model based on smart metering and demand-side management

Meysam Doostizadeh, Hassan Ghasemi*

The School of Electrical and Computer Engineering, University of Tehran, Iran

A R T I C L E I N F O

Article history:
Received 3 April 2012
Received in revised form
18 August 2012
Accepted 20 August 2012
Available online 24 September 2012

Keywords:
Smart metering
Day-ahead real-time pricing
Demand-side management

A B S T R A C T

Several factors support more deployment of real-time pricing (RTP); including recent developments in the area of smart metering, regulators interest in promoting demand response programs and well-organized electricity markets. This paper first reviews time-based electricity pricing and the main barriers and issues to fully unleash benefits of RTP programs. Then, a day-ahead real-time pricing (DA-RTP) model is proposed, which addresses some of these issues. The proposed model can assist a retail energy provider and/or a distribution company (DISCO) to offer optimal DA hourly prices using smart metering. The real-time prices are determined through an optimization problem which seeks to maximize the electricity provider's profit, while considering consumers' benefit, minimum daily energy consumption, consumer response to posted electricity prices, and distribution network constraints. The numerical results associated with Ontario electricity tariffs indicate that instead of directly posting DA market prices to consumers, it would be better to calculate optimal prices which would yield higher benefit both for the energy provider and consumers.

1. Introduction

In traditional power system operation and management, more attention is given to supply side compared to demand, and consumers are assumed to be unwilling or incapable of actively changing their consumption behavior. Therefore, expensive peaking plants are committed to meet demand during peak periods leading to higher generation costs. On the other hand, during off-peak periods, demand is typically covered by cheaper base load plants. Consequently, wholesale prices are highly fluctuating during the year and even within a day. In addition to high variability of market prices, declining reserve margins, transmission congestion, and environmental issues increase the importance of improving the link between supply-side and demand-side.

In most electricity markets, end-use consumers such as residential and small business consumers are entities that purchase energy from a retail energy provider as assumed in this paper and/or a distribution company (DISCO) and they do not participate in the market. These consumers are charged either fixed retail prices for a season or a rate based on time-of-use (TOU) of their energy consumption; they pay higher price during peak period than off-peak period. Thus, there is no economic incentive for consumers to respond to hourly changes in electricity market prices. Some consumers are charged retail prices which reflect wholesale market conditions; the consumers response to these prices would lead to reduce generation cost and improve market efficiency and system reliability.

By recent developments on smart metering technologies and the dire need to increase price-responsive demand, a number of utilities and states have executed a variety of time-based pricing programs. For instance, a day-ahead real-time pricing (DA-RTP) tariff used by the Illinois Power Company in the United States [1], several critical peak pricing pilots in California, Idaho, and New Jersey [2], and the three-level (on-peak, mid-peak, off-peak) TOU pricing tariff in Ontario, Canada [3]. However, recent studies have shown that exposing end-use consumers to hourly real-time prices is known as the most efficient tool that can urge consumers to consume more wisely and efficiently [4]. Given the recent increases in energy prices, RTP provides opportunity to consumers to reduce their energy bills by taking the advantage of lower energy prices in some periods and reducing their consumption when energy prices are high. Although the effectiveness of RTP implementation is widely unanimous, there are some barriers to RTP including technology issues, financial disincentives posed by flat price tariffs, regulatory concerns, and apparent lack of consumer interest. Therefore, some appropriate strategies are required to overcome such obstacles.

* Corresponding author. Tel.: +98 2161114315.
E-mail addresses: m.doostizadeh@ut.ac.ir (M. Doostizadeh), h.ghasemi@ut.ac.ir (H. Ghasemi).
URL: http://ece.ut.ac.ir/faculty/Ghasemi/.

0360-5442/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.energy.2012.08.029

There has been much attention paid to pricing programs in recent years. Theoretical and simulation studies have focused on understanding the economic and technical advantages of these programs [5–9]. The environmental implications of RTP are investigated in [10] and it is shown that RTP can potentially reduce the emission level in many regions in the United States, where peak demand is almost met by oil fired capacity. References [11,12], have proposed an economic load model based on price elasticity of demand in order to simulate consumers response. The impact of RTP on price spikes, peak demand, consumer bill, and power supplier under smart grid concept is investigated in [13]. Reference [14] lays out an analytical framework to evaluate the desirability of smart meter, time varying pricing programs and provision of feedback packages to consumers. The framework is applied to determine the impact of the programs and packages on domestic load profiles. Load adjustment of a given consumer in response to hourly electricity prices is modeled in [15]. An RTP approach is proposed in [16]. The model is used by an energy provider in case of energy shortage; the load reduction is achieved by RTP based on consumers price elasticity in energy shortage period. An RTP method based on a distributed algorithm which manages the interactions between each consumer and the energy provider is proposed in [4]. The algorithm finds the optimal energy consumption levels for each consumer to maximize consumers' benefit and to minimize the cost charged to the energy provider. A composite demand function is introduced in [17] in order to represent the demand model comprising different types of consumers. The model can be utilized by a retailer to offer real-time prices to its consumers. However, the cross-elasticity of consumers, each consumer's benefit, each consumer characteristic, and distribution operation aspects are not considered in the model.

In most of the previous related literature work except [4,16,17], optimal RTP is not discussed. In this paper, considering the main barriers of implementing RTP, it is argued that in RTP programs, sending market prices to consumers would not always achieve the best solution to the energy consumption problem. Therefore, this paper is focused on proposing a new practical RTP model to overcome RTP barriers. The proposed model would help energy provider find optimal hourly DA prices. The objective is to maximize retailer's profit based on DA energy market prices considering demand elasticity and consumers' benefit. In this model, it is assume that each consumer is equipped with a smart meter with a two-way communication [15].

The remaining of this paper is organized as follows: Section 2 provides a brief description of time-based pricing and reviews barriers to RTP. Section 3 presents framework of DA-RTP. Mathematical formulation of the proposed model is presented in Section 4. Section 5 presents and discusses the results of different case studies carried out for a 32-node test system, based on Ontario electricity data and regulated retail prices, to demonstrate the feasibility and effectiveness of the proposed model. The paper is concluded in Section 6.

2. Review of time-based pricing, RTP implementation and barriers

2.1. Categories of time-based pricing programs

Various time-based pricing structures are discussed in this section. Depending on the type of programs, the price structures can change on an hourly, daily, or longer time-period basis:

- *Seasonal flat pricing*: In this structure, prices are fixed within a season but may change from one to another.
- *Time-of-use pricing*: In this structure, prices are fixed within each TOU pricing period. Pricing periods are defined according to time of day, day of week, and/or season. However, since TOU rates are fixed and are announced months earlier, they do not provide incentives for consumers to respond to wholesale hourly electricity prices.
- *Critical peak pricing*: Similar to TOU rates, prices are fixed across block of time in this structure. However, the price for at least one period has the potential to change daily, either based on an occasion or regularly, which are announced on a day-ahead or hour-ahead basis.
- *Peak day rebates*: In this structure, consumers receive electricity bill rebates for not using power during peak periods, and they remain on their standard tariff even during critical events.
- *Real-time pricing*: In this structure, energy prices applied to consumers vary hourly to reflect wholesale market prices. Prices are typically announced a day or an hour before the actual time of energy delivery to consumer. Based on the method of hedging price risk and/or revenue assurance, several versions of RTP have been tested by utilities.

These pricing structures are characterized by different features depending on how they reflect wholesale prices, and how can affect both consumers and energy providers willingness to adapt these programs. Among these pricing structures, RTP can track the pattern of wholesale energy prices and can provide opportunity to consumers to reduce their energy bills by taking advantage of lower energy price periods and reducing their consumption during peak periods. However, it might be too complicated to implement or might involve much risk for consumers along with other difficulties mentioned below.

2.2. Barriers to RTP

Although the benefits of RTP programs are widely known, the installation level of these programs is still low. Typically, a limited number of commercial and industrial consumers are provided with RTP. The implementation level of these programs to residential consumers is even lower. The barriers to RTP include technology issues along with several concerns on all involved parties, including regulators, consumers, utilities and energy providers:

- Technology issues including the lack of smart metering, and communication and control systems which support RTP.
- Regulatory concerns: In the distribution sector, the regulation goal is to provide distribution companies with incentives to recover their investment and efficient operation, and to guarantee that consumers benefit from the obtained efficiency [18]. Furthermore, a good regulation balances different stakeholders' interests in the short-term such as returns and tariffs, and identifies these interests convergence in the long-term [19]. Licensing, controlling and monitoring of energy activities, setting and implementing tariffs and customer protection are the main functions of the regulatory system [20]. Therefore, regarding RTP implementation, regulator are concerned about metering installation cost and pricing mechanism that would entail fairness towards consumers and energy providers in terms of their energy bills and benefits encouraging efficient energy consumption.
- Energy providers and utilities financial disincentives:
  - Utility benefit from RTP: Utilities are concerned about whether the potential benefits from consumers energy management under RTP, such as capital investment deferral, maintenance cost reduction in long-term can outweigh possible short-term revenue reduction or not.

  – Recovery of fixed cost: This can be a concern in case of expecting that fixed costs would not be recovered through volumetric energy charges.
  – Consumer bill impact and loss of revenue: Energy providers are concerned about the potential revenue losses from free riders' activities (i.e. consumers who receive immediate bill reduction due to their normal load patterns which may coincide with low price hours).
- Apparent lack of knowledge and interest among consumers in RTP: Most of the consumers seem to prefer simple flat tariff rather than real-time prices due their unwillingness to either sacrifice their comfort level or not seeing enough financial benefits in adapting to RTP. Also, some consumers are unwilling to take the RTP risks even though they might achieve reduced bill.

3. Framework of the proposed RTP

In this section, a general framework is proposed which will address some of the mentioned difficulties above. The proposed framework is basically based upon smart grid concept. As it is depicted in Fig. 1, in a smart environment, each consumer is equipped with a smart meter and an energy management system that schedules his/her energy consumption in response to real-time prices. The meters are connected to the utility through a communication network such as local area network that allows two-way communication between electricity provider and the meter. With this capability, beside receiving real-time prices from the electricity provider, the electricity provider would have access to real-time information on the electricity consumption of each consumer.

In this framework, regulatory authority instead of determining fixed electricity rates, provides energy providers with the means to determine electricity prices such that both consumers and energy providers interests are promoted. The energy provider uses DA market prices, distribution network data, and consumers load data to optimally determine DA prices which will be sent to consumers through smart metering infrastructure. These prices are determined such that the consumers adapted to RTP will respond to the posted prices in a way that both energy provider and consumer will benefit as explained with detailed mathematical formulation in the next section.

The proposed framework alleviates the mentioned barriers effectively as discussed next. Some of the challenges such as technology issues and their corresponding costs can be met with the recent development in smart metering technology; however, others should be analyzed more specifically. The latter group of challenges is categorized into three following groups:

- *Regulatory concerns*: Fairness and efficiency are two traditional regulatory concerns in tariff design mechanism. These concerns exist for the RTP as well. The proposed framework can address some of these concerns by ensuring that each consumer under the proposed pricing scheme would pay less or equal to the case that market prices are used.
- *Energy provider and utilities financial disincentives*: Instead of using fixed ¢/kWh for monthly consumption, by having peak consumption of each consumer and multiplying it by this rate, a direct signal is sent to consumers indicating that they should avoid using all their appliances directly. The proposed framework has two key advantages which address RTP implementation and consumer bill impact on utility benefit. The first advantage of this framework is that the energy provider is able to maximize its profit by determining the optimized DA real-time prices. Furthermore, consumers load characteristics are considered in determining these prices preventing revenue losses from free riders activities.
- *Consumers resistance*: To encourage more consumers to adapt RTP, they should be offered fair prices which do not impose notable amount of risk on them. In the proposed framework, real-time prices are determined based on market prices, regulated tariffs and considering a price cap. This would ensure that real-time market prices will not be directly transferred to consumers, avoiding high risk to them leading to increased consumer satisfaction.

4. Mathematical formulation

The proposed model to determine the optimal real-time prices seeks to maximize the profit of an energy provider which supplies electricity to all consumers connected to the distribution network. In order to correctly model consumers consumption behavior, several aspects are considered here including consumers benefit, minimum daily energy consumption and consumer response to DA real-time prices represented by means of an economic demand model. Distribution network constraints are also taken in the proposed model into account. The mathematical formulation of the proposed framework is described as follows.

4.1. Objective function

The objective function is formulated as (1) here. It aims to maximize the energy provider's profit, which is defined as the difference between its revenue due to selling energy to consumers and the cost of purchasing energy from the electricity market.

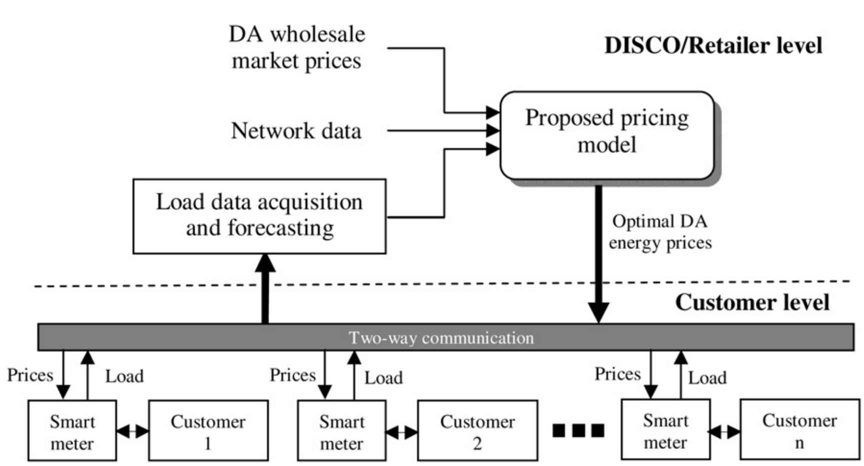

Fig. 1. Proposed DA pricing framework.

However, it is good to mention that beside short term operational aspects, the energy provider can also consider other (short-term and/or long-term) business objectives while constructing his/her objective function.

$$\text{Max} \sum_{t=1}^{24} \left\{ \left[\sum_{c=1}^{n_c} d_c(t) \cdot \rho_c(t) \right] - P_{\text{sub}}(t) \cdot \rho_E(t) \right\} \tag{1}$$

where $P_{\text{sub}}(t)$ is the amount of power purchased by the energy provider from energy market through main transformers at Hour t; $\rho_E(t)$ is the energy market price at Hour t; $d_c(t)$ represents customer response to energy prices (kWh); $\rho_c(t)$ is the DA energy price announced by energy provider and communicated to each customer through smart meter (¢/kWh); and n_c is the number of customers.

4.2. Constraints

The constraints which have to be respected on the daily operation of the network are categorized into seven groups as explained below.

4.2.1. Consumer response to DA energy prices

Each consumer as an entity can manage its consumption independent from others and the energy demand of each consumer can vary based on its characteristics. Different types of consumers may have different response to the same price. For instance, a household consumer response to price changes is different from that of an industrial consumer. The behavior of each consumer can be modeled through its utility or benefit function. In response to changes to energy prices, each consumer tries to adjust its power consumption to maximize its own welfare. Also, electrical loads can be categorized into shiftable and non-shiftable loads. The first category is assigned to loads which can be operated at any time throughout a day or particular time window (e.g. dish washer). The second one refers to loads that cannot be shifted in a day (e.g. illuminating load and HVAC).

Reference [11] discusses the detailed process of modeling and formulating how the RTP program affects electricity demand and how the maximum benefit of consumers is achieved during a day with hourly intervals. The final responsive economic demand model in time interval t is presented by:

$$d_c(t) = d_{0c}(t) \left\{ 1 + \frac{\varepsilon_c(t) \cdot [\rho_c(t) - \rho_{0c}(t)]}{\rho_{0c}(t)} + \sum_{\substack{h=1 \\ h \neq t}}^{24} \varepsilon_c(t,h) \frac{[\rho_c(h) - \rho_{0c}(h)]}{\rho_{0c}(h)} \right\} \tag{2}$$

where $\varepsilon_c(t)$ and $\varepsilon_c(t,h)$ are self and cross price elasticity of the demand, respectively; $\rho_{0c}(t)$ is base energy price (tariff) set by the regulator for a season (¢/kWh); and $d_{0c}(t)$ is the initial demand forecast (kWh).

Therefore, the active consumers response to offered DA real-time prices ($\rho_c(t)$) according to its initial load level and initial retail energy prices can be modeled as (2). It is worth mentioning that at each hour, initial demands are known and DA real-time prices are the variables to be determined in the optimization process.

4.2.2. Maximum and minimum demand limits

Considering realistic consumers response, one can say that the consumption is not totally flexible; consequently, the following constraints are taken into account in our model. Hence, maximum and minimum demand limits should be considered for each load as it is stated in the Equation (3). Minimum load level $d_c^{\min}(t)$ refers to the load of appliances which always need to be on during the operating horizon, and maximum load level $d_c^{\max}(t)$ refers to the total power consumption level of consumer's appliances assuming that all available appliances are on during the scheduling hours.

$$d_c^{\min}(t) \le d_c(t) \le d_c^{\max}(t) \tag{3}$$

4.2.3. Minimum daily consumption

Minimum daily consumption required by each consumer is represented by (4).

$$\sum_{t=1}^{24} E_c(t) \ge E_c^{Day} \tag{4}$$

where $E_c(t)$ is the energy consumption of Consumer c at Hour t; E_c^{Day} is the minimum daily consumption used by Consumer c.

4.2.4. Price cap

As mentioned in Section 3, a maximum limitation for real-time price has to be considered to hedge consumers against high energy prices.

$$\rho_c(t) \le \rho_c^{\max}(t) \tag{5}$$

where $\rho_c^{\max}(t)$ is the price cap for real-time prices. This can be different value for residential, industrial and commercial consumers.

4.2.5. Limit on energy provider's revenue from each consumer

Although the previous constraint protects consumers from being offered very high prices, another constraint is required to avoid offering relatively high prices at most hours of a day by the energy provider with the aim of maximizing energy provider's benefit. Therefore, energy provider's revenue from selling energy to each consumer under the proposed pricing model should be less or equal to the case that market prices are directly sent to consumers. This will change demand curve in a way leading to win–win situation for both the energy provider and consumers. In addition, (6) can provide incentive to consumers to actively participate in each hour and respond to hourly prices. For instance, $K = 0.95$ (payment coefficient) indicates that each consumer's bill will be less than or equal to 95% of the case when market prices are applied to each consumer.

$$\sum_{t=1}^{24} d_c(t) \cdot \rho_c(t) \le K \cdot \sum_{t=1}^{24} d_{c_E}(t) \cdot \rho_E(t) \tag{6}$$

where $d_{c_E}(t)$ is consumer response to DA market prices.

4.2.6. System adequacy constraint

This is necessary to ensure that there is enough capacity to meet the hourly demand forecast as well as maintaining a reserve margin:

$$P_{\text{Sub}}^{\max} \ge \text{RES}(t) + \sum_{c=1}^{n_c} d_c(t) \tag{7}$$

where $RES(t)$ is adequacy reserve maintained by the energy provider; and $P_{\text{Sub}}^{\max}$ is the active power capacity of substation transformer.

4.2.7. Distribution network constraints

In this study, it is considered that the energy provider is responsible for network operation. Therefore, the reliability and security of the network have to be taken into consideration. Besides, the RTP program can provide the opportunity for network operator to deal with the cases when the reliability of network is jeopardized. This can be done by offering appropriate real-time prices to consumers. The network operation constraints are as follows (as described in [21]):

- Real power flow equations:

$$P_{\text{inj}}(t) = \sum_{j=1}^{N} |V_{t,i}||V_{t,j}||Y_{i,j}|\cos(\delta_{t,j} - \delta_{t,i} + \theta_{i,j}); t = 1, \ldots, 24 \tag{8}$$

- Reactive power flow equations:

$$Q_{\text{inj}}(t) = -\sum_{j=1}^{N} |V_{t,i}||V_{t,j}||Y_{i,j}|\sin(\delta_{t,j} - \delta_{t,i} + \theta_{i,j}); t = 1, \ldots, 24 \tag{9}$$

- Feeders flow limits:

$$\left|S_{t,ij}(V_t, \delta_t)\right| \le S_{t,ij}^{\max} \tag{10}$$

- Bus voltage limits:

$$V_i^{\min} \le V_{t,i} \le V_i^{\max} \tag{11}$$

- Substation capacity limit:

$$P_{\text{sub}}(t) \le P_{\text{sub}}^{\max} \tag{12}$$

where $|V_{t,i}|$ is voltage amplitude at node i; $\delta_{t,i}$ is voltage angle at node i; $|Y_{i,j}|$ is element (i,j) in admittance matrix; $\theta_{i,j}$ is angel of $|Y_{i,j}|$; $P_{\text{inj}}(t)$ is the net injected active power to node i; $Q_{\text{inj}}(t)$ is the net injected reactive power to node i; $S_{t,ij}$ is the apparent power flow from node i to node j; $S_{t,ij}^{\max}$ is the capacity of the line/cable between node i and node j; $V_i^{\max}$ and $V_i^{\min}$ are maximum and minimum voltage magnitude at node i, respectively; and N is the total number of nodes.

4.3. Solution method

The proposed model addressed in this paper is formulated as a non-linear programming (NLP) problem. In order to make the proposed model applicable for real size distribution networks with large number of consumers, a fast and robust optimization technique known as Benders decomposition is applied in this study. The Benders decomposition algorithm [22] is a partitioning technique on two levels (master problem and subproblem) which utilizes an iterative procedure between both levels in order to obtain an optimal solution. The master problem determines real-time prices by ignoring network constraints, whereas the subproblem deals with checking network physical constraints. Master problem solution is transferred to the subproblem, which verifies the feasibility of the master problem solution and provides marginal data and dual values associated with the given variables by the master problem previously. More detailed on benders decomposition is available in [23].

This method allows us to appropriately divide the problem into two smaller problems which are easier to solve. Fig. 2 depicts the procedure including the steps.

4.3.1. Master problem

The master problem's objective function is formulated as:

$$\text{Max} \sum_{t=1}^{24} \left\{ \left[\sum_{c=1}^{n_c} d_c(t) \cdot \rho_c(t) \right] - P_{sub}(t) \cdot \rho_E(t) \right\} - \sum_{t=1}^{24} \alpha_t^* \tag{13}$$

Subject to constraints (2)–(7) and the Benders cuts:

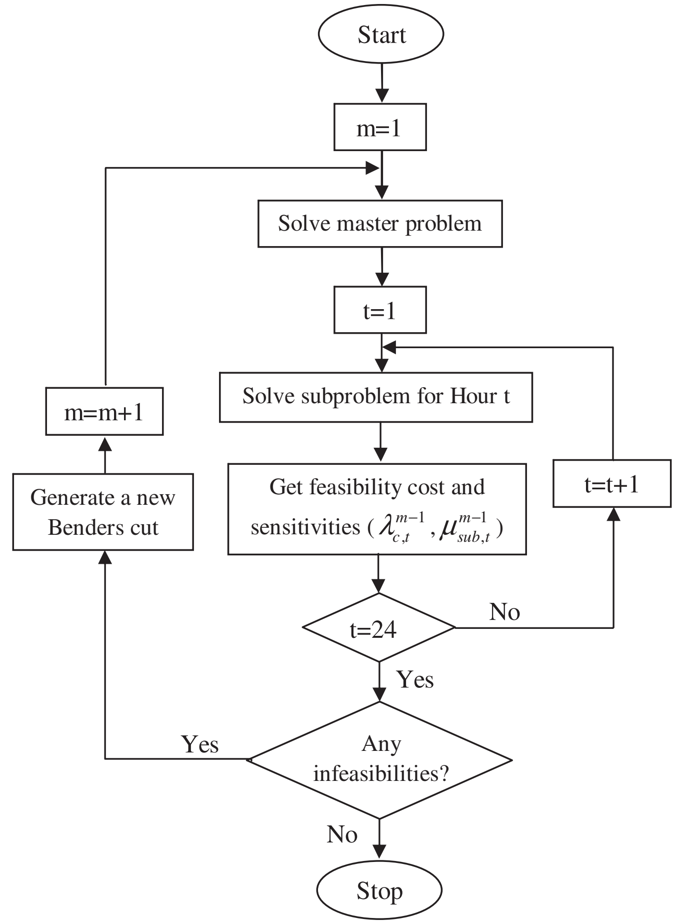

Fig. 2. Benders decomposition flowchart.

$$\alpha_t^* \ge \alpha_t^{m-1} + \sum_{c=1}^{n_c} \lambda_{c,t}^{m-1} \left(d_c(t) - \overline{d}_c(t)^{m-1} \right) + \mu_{\text{sub},t}^{m-1} \left(P_{\text{sub}}(t) - \overline{P}_{\text{sub}}(t)^{m-1} \right) \tag{14}$$

where α_t^* is the subproblem cost at iteration $m-1$.

The first term of the objective function represents the energy provider's profit. The second term represents feasibility costs of each hourly subproblem. The Benders linear cuts (14) couple master and subproblem, and are updated at each iteration.

4.3.2. Subproblem

The subproblem checks the feasibility of the master problem solution by mean of an AC power flow. Then, any violations in constraints (10)–(12) can be relieved by adjusting the imported power through substation $P_{sub}(t)$ and customers' demand $d_d(t)$. The objective function introduced in (15) minimizes the cost of deviations from the master problem solution ($\overline{P}_{\text{sub}}(t)$ and $\overline{d}_c(t)$ which are fixed by the master problem):

$$\text{Min} \sum_{i=1}^{N} \text{Pup}_i(t) + \text{Pdn}_i(t) + \text{Qup}_i(t) + \text{Qdn}_i(t) \tag{15}$$

where $Pup_i(t)$, $Pdn_i(t)$, $Qup_i(t)$ and $Qdn_i(t)$ are slack variables of the optimization problem added to AC power flow equation in order to make the subproblem feasible.

It is subjected to the constraints (10)–(12) and:

$$P_{\text{inj}}(t)+\text{Pup}_i(t)-\text{Pdn}_i(t)=\sum_{j=1}^{N}|V_{t,i}||V_{t,j}||Y_{i,j}|\cos(\delta_{t,j}-\delta_{t,i}+\theta_{i,j});\quad t=1,\ldots,24 \tag{16}$$

$$Q_{\text{inj}}(t)+\text{Qup}_i(t)-\text{Qdn}_i(t)=-\sum_{j=1}^{N}|V_{t,i}||V_{t,j}||Y_{i,j}|\sin(\delta_{t,j}-\delta_{t,i}+\theta_{i,j});\quad t=1,\ldots,24 \tag{17}$$

$$d_c(t) = \overline{d}_c(t)^m \leftrightarrow \lambda_{c,t}^{m-1}; P_{\text{sub}}(t) = \overline{P}_{\text{sub}}(t)^m \leftrightarrow \mu_{\text{sub},t}^{m-1} \tag{18}$$

Constraint (18) provides the marginal data ($\lambda_{c,t}$ and $\mu_{sub,t}$) of the master problem solution ($\overline{d}_c(t)$, $\overline{P}_{\text{sub}}(t)$) at the same iteration. The marginal data are used in the benders cuts formulation as shown in (14). The subproblem cuts are updated in each iteration in order to improve new master problem solution and this iterative procedure continues until the master problem solution is feasible.

5. Simulation results

The results of applying the proposed DA-RTP model to a 32-node radial distribution system shown in Fig. 3 [24] are presented and discussed in this section. Due to the importance of accurate knowledge of consumers behavior, loads are characterized based on consumer type. Each consumer belongs to one of the 3 categories (residential, commercial, and industrial). The test system includes 320 consumers (10 consumers at each node). The consumers at each node are assumed to be the same type (residential, commercial and industrial) as presented in Table 1. Each day is divided into 3 time intervals (on-peak, mid-peak, and off-peak) as used in Ontario, Canada [3]. The elasticity values for each type of consumer at the 3 mentioned time intervals are prudently derived from [25,26], and are shown in Table 2. The DA energy prices and load forecasts on a typical winter and summer day (February 4 and August 4, 2011) are used from the wholesale electricity market data of Ontario, Canada [27] to analyze the feasibility of the proposed DA-RTP model on the test case (Fig. 4). In this case, the demand curve for Ontario market is scaled down to be used at the test system which is a distribution system. The daily load curve and the contribution of each type of consumers to overall system energy usage are shown in Fig. 5.

The optimization problem described in Section 4 is an NLP problem solved by GAMS [28]. CONOPT solver is used to solve the NLP master problem and subproblem. The solution obtained by CONOPT is found by means of the application of the generalized reduced gradient algorithm specifically designed for large nonlinear programming problems [29].

5.1. Different pricing methods

Three cases are discussed in the simulations. Case A represents the currently used regulated pricing mechanism in Ontario, Canada. Case B examines the impact of directly sending DA wholesale market prices to consumers. Finally, Case C presents the results of posting optimal DA prices calculated by the proposed pricing model.

5.1.1. Case A: the currently used regulated price plan

Although each local distribution company or electricity retailer in Ontario uses a slightly different bill format and terminology for its consumers, components of the consumer bill are the same including electricity rates, distribution rates, transmission rates, regulatory charge, and debt retirement charge. The electricity rates which represent the supply costs are set by the Ontario Energy Board as part of the Regulated Price Plan (RPP) [30]. If a consumer purchases electricity from an electricity retailer, the prices paid by the consumer will be different and will be stated in the contract signed by the consumer and retailer. In addition, the supply cost of electricity provided to RPP consumers is determined in accordance with the rules established by legislation. The wholesale consumers, however, pay according to hourly Ontario electricity prices. At the end of each month, an adjustment amount referred to as the global adjustment is applied to all electricity consumers [30]. The average market prices during February and August were 3.3 ¢/kWh and 3.5 ¢/kWh, respectively. Also, the average global adjustments were 3.5 ¢/kWh and 3.6 ¢/kWh during February and August 2011, respectively [27]. Therefore, average RPP prices were 6.8 ¢/kWh and 7.1 ¢/kWh during February and August 2011, respectively as reported in [3]. The average RPP prices are assumed as base energy price (tariff) in the numerical studies.

5.1.2. Case B: sending DA market prices to consumers

In this case, it is assumed that 40% of consumers participate in the RTP program. However, the RTP rate for each hour equals to sum of DA energy market price for that hour and global adjustment (Fig. 6). Note that maximum and minimum demand limits are equal to 115% and 85% of the initial load forecasts, respectively, which is consistent with [26]. Active consumers response to DA energy market prices according to their initial consumption curve and base electricity price (i.e. RPP) is shown in Fig. 7. As it can be seen in

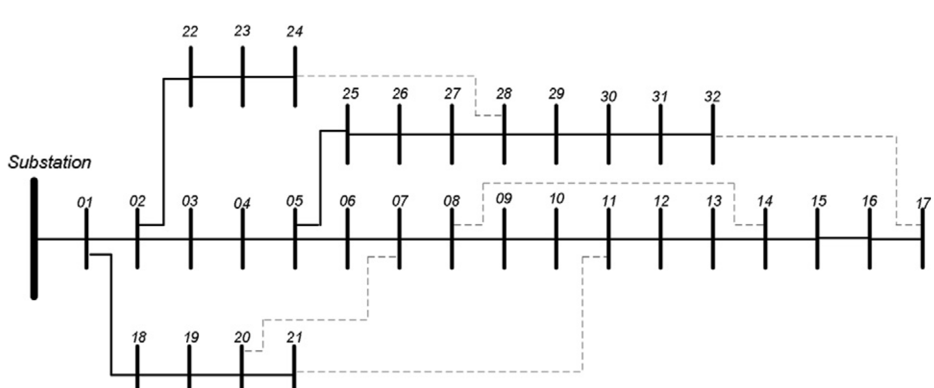

Fig. 3. The 32-node radial distribution network.

Table 1
Load types at different buses of the 32-node distribution test system.

Type of consumer	Load buses
Residential	2,4,5,8,9,10,11,12,14,15,16,17,18,19,20,21,22,25,26,27,32
Commercial	1,3,6,7,13,28,29,30,31
Industrial	23,24

Table 2
Self and cross elasticities.

Type of consumer		On-peak[a]	Mid-peak[a]	Off-peak[a]
Residential	On-peak	−0.150	0.080	0.070
	Mid-peak	0.080	−0.140	0.050
	Off-peak	0.070	0.050	−0.120
Commercial	On-peak	−0.180	0.070	0.050
	Mid-peak	0.070	−0.170	0.030
	Off-peak	0.050	0.030	−0.160
Industrial	On-peak	−0.180	0.100	0.080
	Mid-peak	0.100	−0.180	0.060
	Off-peak	0.080	0.060	−0.160

Winter: on-peak (7–11,17–19); mid-peak (11–17); off-peak(19–7).
[a] Summer: on-peak (11–17); mid-peak (7–11,17–19); off-peak(19–7).

Fig. 7, with RTP implementation, consumers energy consumption during peak hours would be reduced. However, it is seen that load shifting to off-peak hours is insignificant. This is due to the fact that little difference exists between market prices and the base energy price during the day which does not provide strong incentive for consumers to change their demand profile.

5.1.3. Case C: sending optimal DA real-time prices

In this case, similar to Case B, it is assumed that 40% of consumers participate in the RTP program. The maximum and minimum demand limits are the same as before. In addition, it is assumed that minimum daily consumption required by each consumer is 90% of its initial consumption and the payment coefficient (K) is assumed 1. The effect of changing K is discussed later in this section. In this case, the optimal real-time prices offered by energy provider to each type of consumer are calculated based on the proposed model as depicted in Fig. 6. As it is evident, the energy provider offers low energy prices during off-peak period in order to encourage consumers shift part of their demand to this period. It is worth mentioning that variations exist in RTP of different consumer types in several hours. Customers' load characteristic is the main reason for these variations. According to Equation (2), consumers' response to offered DA energy prices depend on their initial load level and their price elasticities which are different for each type of consumer. Fig. 7 also shows the impact of offered optimal prices on daily demand. Compared to Case B, by posting optimal DA real-time prices, consumers energy consumption during peak hours would be reduced more and a larger amount of consumers demand is shifted to off-peak hours.

To compare the proposed model with Cases A and B, the results are analyzed from economical and technical points of view. Technical criteria such as peak load reduction, load factor, peak to valley distance, and distribution losses are also presented in Table 3. As it can be seen from Table 3, all considered technical criteria are improved after implementing the proposed RTP model. Therefore, using the proposed RTP model would enhance the reliability of energy delivery and the efficiency of grid operation. Some economic criteria such as energy purchasing cost from the wholesale market, consumers bill, and energy provider profit are reported in Table 4. Table 4 shows that economical criteria are improved for the proposed model as well. The cost of purchasing energy from market is decreased compared to Cases A and B. It is important to mention that although energy provider's revenue from selling energy to consumers (i.e. consumers bill) is limited to the case that market prices are used (Case B), energy provider's profit in the proposed model is increased and consumers energy consumption is

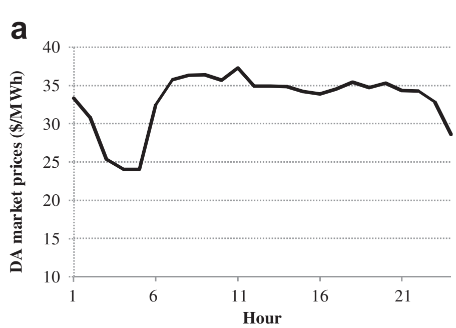

Fig. 4. DA energy market prices: (a) February 4th, 2011 (b) August 4th, 2011.

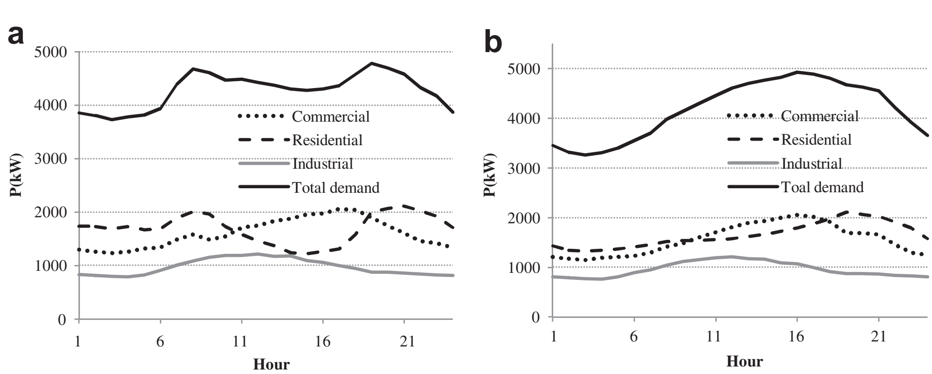

Fig. 5. Daily demand curves (residential, commercial, and industrial): (a) February 4th, 2011 (b) August 4th, 2011.

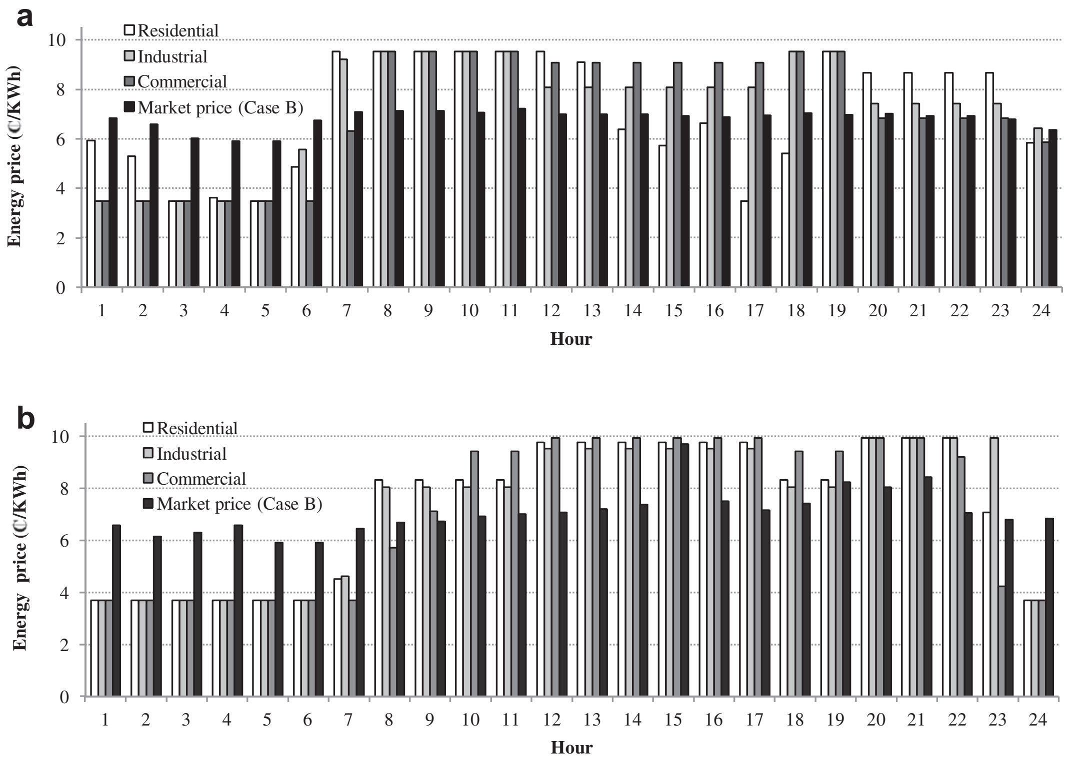

Fig. 6. Optimal DA prices: (a) February 4th, 2011 (b) August 4th, 2011.

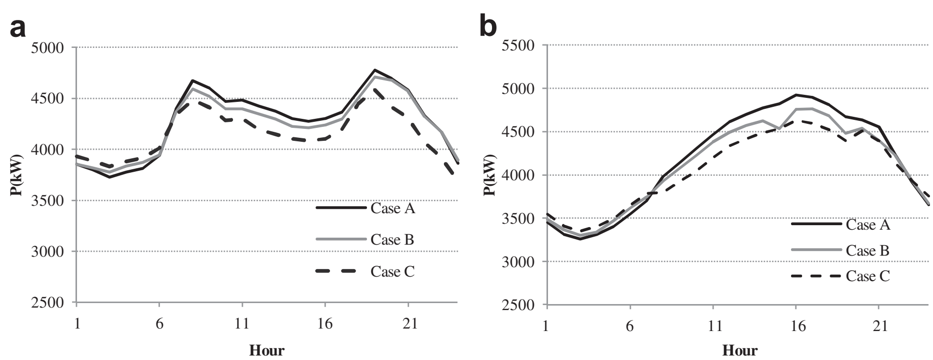

Fig. 7. Hourly demand under different cases: (a) February 4th, 2011 (b) August 4th, 2011.

Table 3
Technical indicators for case studies; ($K = 1$).

	Peak reduction (kW)		Load factor (%)		Peak to valley distance (kW)		Distribution network losses (kWh)		Total energy consumption (kWh)	
	Feb. 4	Aug. 4	Feb. 4	Aug. 4	Feb. 4	Aug. 4	Feb. 4	Aug. 4	Feb. 4	Aug. 4
Case A	–	–	89.5	84.6	1048.4	1662.4	5282.2	5109.7	102,557.0	100,011.3
Case B	66.0	162.4	90.1	86.3	933.3	1457.2	5212.8	4963.5	101,831.4	98,618.9
Case C	192.6	295.4	90.5	87.5	897.3	1217.5	4993.7	4819.0	99,533.4	97,220.3

Table 4
Economic indicators for case studies; ($K = 1$).

	Energy purchasing cost ($)		Energy provider's profit ($)		Customers' bill ($)	
	Feb. 4	Aug. 4	Feb. 4	Aug. 4	Feb. 4	Aug. 4
Case A	3629.7	3804.5	3344.1	3306.3	6973.8	7110.8
Case B	3599.4	3743.2	3334.7	3273.9	6934.1	7017.1
Case C	3476.0	3632.6	3458.1	3384.5	6934.1	7017.1

decreased compared to Case B. The reason is that by posting optimal DA real-time prices, consumers are encouraged to reduce demand and/or shift demand to low price periods when the energy market price is high as well as having lower network losses.

5.2. The impact of level of smart meter deployment

This is the same as Case C except 80% of consumers respond to prices posted by the energy provider. As it can be seen in Fig. 8,

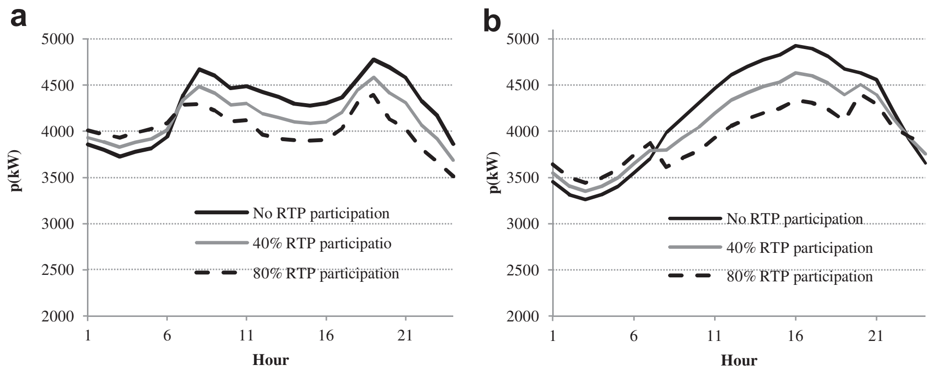

Fig. 8. The impact of level of smart meter deployment on demand curve: (a) February 4, 2011 (b) August 4, 2011.

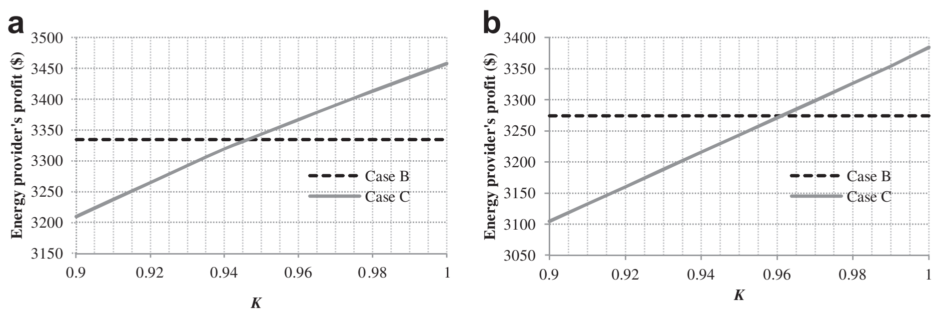

Fig. 9. The impact of changing *K* on energy provider's profit: (a) February 4, 2011 (b) August 4, 2011.

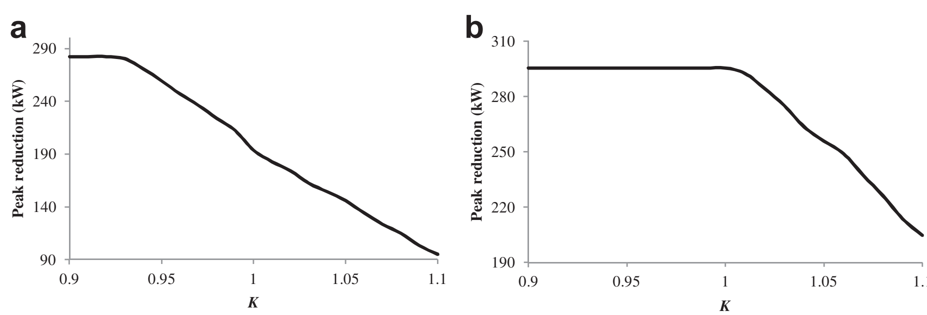

Fig. 10. The impact of changing *K* on peak reduction: (a) February 4, 2011 (b) August 4, 2011.

a greater portion of demand during peak hours is reduced and also load shift to off-peak hours is increased by having more consumers participating in the RTP program. In addition, energy provider's profit is increased significantly up to \$3536.3 in February 4 and \$3424.8 in August 4.

5.3. The impact of limit on energy provider's revenue from each consumer

In this case, it is focused to analyze the impact of limiting energy provider's revenue from each consumer (Equation (6)). As it was mentioned in Section 4.2, in order to protect consumers' right, energy provider's revenue from selling energy to each consumer under the proposed pricing model should be less or equal to the case that market prices are directly sent to consumers; therefore, in our model K is always less or equal to 1. Energy provider's profit obtained for different values of K (from 0.9 to 1) is depicted in Fig. 9. As it can be seen from Fig. 9, energy provider's profit for $K \geq 0.946$ in February 4 and $K \geq 0.961$ in August 4 is greater than its profit in the case that market prices are directly sent to consumers (Case B). Therefore, this can be an efficient tool for energy provider to provide more incentive to consumers to actively respond to hourly prices. On the other hand, the service provider not only can improve his profit, but also he can meet other business objectives by including them in (1). Obviously, using values beyond 1 for K would increase energy provider's profit. Case C is simulated for K beyond 1 and the results show that by increasing K, energy provider would offer relatively high prices at most hours of the day. Also, the peak reduction would decrease (Fig. 10). This is due to the fact that posting high prices at most hours would not provide strong incentive for consumers to shift part of their consumption and they would only reduce some part of their demand at most hours of the day.

6. Conclusions

In this paper, within the context of smart grids, a novel day-ahead real-time pricing model is presented. The regulatory authority provides energy providers with the means to determine electricity prices such that both consumers and energy providers interests can be promoted. By using the proposed pricing model, each energy provider seeks to meet his/her business objectives (e.g. maximize profit) through offering optimal DA prices to consumers. The energy provider optimally determines hourly DA prices considering DA market prices, consumers' consumption behavior and distribution network data. These prices are then sent to consumers equipped with smart meters, energy management systems and a two-way communication. The proposed DA-RTP model has been applied to a distribution test system with 320 consumers along with demand and market price curves of Ontario, Canada and its currently used regulated tariffs. The results indicate that applying the DA-RTP model results in flatter demand curve, lower losses, lower peak to peak distance and higher load factor. Moreover, compared to the case that DA market prices are posted to consumers, several economic indicators such as energy purchasing cost from the wholesale market, consumers' bill, and the energy provider's profit can be improved as well. This pricing model provides an opportunity to better utilize the strength of smart grids in distribution systems.

References

[1] Ameren Services. Real-time pricing for residential customers. Available at: http://www.ameren.com/sites/aiu/ElectricChoice/Pages/ResRealTimePricing.aspx; [accessed July 2012].

[2] Edison Electric Institute. Retail electricity pricing and rate design in evolving markets. Available at: http://www.eei.org/ourissues/electricitydistribution/Documents/Retail-Electricity-Pricing.pdf; July 2007 [accessed July 2012].

[3] Ontario Energy Board (OEB), Ontario, Canada, http://www.ontarioenergyboard.ca/OEB/ Consumers/Electricity/Electricity+Prices; [accessed July 2012].

[4] Samadi P, Mohsenian-Rad A, Schober R, Wong V, Jatskevich J. Optimal real-time pricing algorithm based on utility maximization for smart grid. First IEEE International Conference on Smart Grid Communications (SmartGridComm); 2010.

[5] Borenstein S. The long-run effects of real-time electricity pricing. Center for the study of energy markets, Working paper 133; 2004. Available at: http://www.ucei.berkeley.edu/PDF/csemwp133.pdf; [accessed July 2012].

[6] Wolak F. Residential customer response to real-time pricing: the anaheim critical peak pricing experiment. Department of Economics Stanford University. Available at: ftp://zia.stanford.edu/pub/papers/anaheim-cpp.pdf; 2006 [accessed July 2012].

[7] Burke W, Auslander D. Residential electricity auction with uniform pricing and cost constraints. North american power symposium (NAPS); October 2009.

[8] Centolella P. The integration of price responsive demand into regional transmission organization (rto) wholesale power markets and system operations. Energy 2010;35(4):1568–74.

[9] Alexander B. Smart meters, real time pricing, and demand response programs: implications for low income electric customers. Oak Ridge Natl. Lab., Tech. Rep., February 2007. Available at: http://www.smartgridinformation.info/pdf/2438-doc-1.pdf; [accessed July 2012].

[10] Holland S, Mansur E. Is real-time pricing green? The environmental impacts of electricity demand variance. Review of Economic Statistics 2008;90(3):550–61.

[11] Aalami HA, Moghaddam M, Yousefi GR. Demand response modeling considering interruptible/curtailable loads and capacity market programs. Applied Energy 2010;87(1):243–50.

[12] Moghaddam M, Abdollahi A, Rashidinejad M. Flexible demand response programs modeling in competitive electricity markets. Applied Energy 2011; 88(9):3257–69.

[13] Valenzuela J, Thimmapuram PR, Kim J. Modeling and simulation of consumer response to dynamic pricing with enabled technologies. Applied Energy 2012; 96:122–32.

[14] Olmos L, Ruester S, Liong S, Glachant J. Energy efficiency actions related to the rollout of smart meters for small consumers, application to the Austrian system. Energy 2011;36(7):4396–409.

[15] Conejo A, Morales J, Baringo L. Real-time demand response model. IEEE Transactions on Smart Grid 2010;1(3):236–42.

[16] Faria P, Vale Z. Demand response in electrical energy supply: an optimal real time pricing approach. Energy 2011;36(8):5374–84.

[17] Yousefi S, Moghaddam M, Majd V. Optimal real-time pricing in an agent-based retail market using a comprehensive demand response model. Energy 2011;36(9):5716–27.

[18] Jamasb T, Pollit M. Benchmarking and regulation of electricity transmission and distribution utilities: lessons from international experience. Cambridge working papers in economics. University of Cambridge. Available at: http://www.dspace.cam.ac.uk/bitstream/1810/280/1/wp0101.pdf; 2004 [accessed July 2012].

[19] Rosenzweig MB, Voll SP, Pabon-Agudelo C. Power sector reform: experiences from the road. The Electricity Journal 2004;17(9):16–28.

[20] Banovac E, Glavic M, Tesnjak S. Establishing an efficient regulatory mechanism - prerequisite for successful energy activities regulation. Energy 2009; 34(2):178–89.

[21] Doostizadeh M, Ghasemi H. Day-ahead scheduling of an active distribution network considering energy and reserve markets. European Transactions on Electrical Power February 2012 [published online].

[22] Benders JF. Partitioning procedures for solving mixed variables programming problems. Numerische Mathematik 1962;4:238–54.

[23] Shahidehpour M, Fu Y. Tutorial: benders decomposition in restructure power systems. Available at: http://motor.ece.iit.edu/ms/benders.pdf; 2005 [accessed July 2012].

[24] Baran ME, Wu FF. Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Transactions on Power Delivery 1989;4(2).

[25] Deal K. Assessing whether firm day-ahead prices lead to changes in elasticity of demand and greater customer efficiencies. Available at: http://www.ieso.ca/imoweb/pubs/mear/Deal-Mountain-Report-April2008.pdf; April 2008 [accessed July 2012].

[26] US Department of Energy. Benefits of demand response in electricity markets and recommendations for achieving them. Report to the United States Congress. Available at: http://eetd.lbl.gov/EA/EMS/reports/congress-1252d.pdf; February 2006 [accessed July 2012].

[27] Independent Electricity System Operator (IESO), Ontario, Canada, http://www.ieso.ca/; [accessed July 2012].

[28] GAMS Development Corporation, General algebraic modeling system (GAMS). Available at: http://www.gams.com; [accessed July 2012].

[29] CONOPT Solver. Available at: http://www.gams.com/dd/docs/solvers/conopt.pdf; [accessed July 2012].

[30] Ontario Energy Board (OEB). Regulated price plan manual. Available at: http://www.ontarioenergyboard.ca/OEB/Documents/EB-2004-0205/RPP-Manual.pdf; August 2011 [accessed July 2012].