Dynamic Pricing

An Efficient Solution for True Demand Response Enabling

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Dynamic pricing: An efficient solution for true demand response enabling

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A dynamic pricing scheme, also known as real-time pricing (RTP), can be more efficient and technically beneficial than the other price-based schemes (such as flat-rate or time-of-use pricing) for enabling demand response (DR) actions. Over the past few years, the advantages of RTP-based schemes have been extensively discussed for DR purposes in electricity markets; however, they have not been proven mathematically according to a valid economics-based model. Instead, most of the related literature has only relied on observations and experiences in the markets of other commodities. Thus, to provide a reliable reference point based on mathematical models, this paper utilizes well-known economic theories and mathematical formulations to prove the impact of RTP on true enabling of DR actions in electricity markets. Based on the theory of saving under uncertainty, it is shown that the use of dynamic pricing can lead to increased willingness of consumers to participate in DR programs which in turn improve the operation of liberalized electricity markets. *Published by AIP Publishing.* https://doi.org/10.1063/1.5009106

NOMENCLATURE

a Lowest electricity price available to consumers according to marginal cost of the retailer
b Highest electricity price available to consumers according to price cap
B Budget
d_1 Amount of electricity that can be purchased with D_1
d_2 Amount of electricity that can be purchased with D_2
D_1 Budget to cover consumption of current hour with DR program
D_2 Budget to cover consumption of coming hours with DR program
n_1 Amount of electricity that can be purchased with N_1 \$
n_2 Amount of electricity that can be purchased with N_2 \$
N_1 Budget to cover consumption of current hour without DR program
N_2 Budget to cover consumption of coming hours without DR program
P_1 Price signal at current hour
P_2 Price signal at coming hours
S_1 Saving at current hour
S_2 Saving at coming hours
U_t Utility function
α Elasticity
μ Mean of the continuous uniform distribution
σ Standard deviation of the continuous uniform distribution
σ^2 Variance of the continuous uniform distribution

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I. INTRODUCTION

After restructuring in the electricity industry, demand side management (DSM) programs were divided into two groups:[1,2]

– Energy efficiency improvement programs
– Demand response (DR) programs

DR programs are one of the DSM techniques and become an affordable solution for increasing productivity in the electricity industry.[3–5] DR programs consist of those DSM methods that alter the power consumption levels over time due to the changing electricity prices. As defined by Federal Energy Regulatory Commission (FERC): "DR is the ability of customers to respond to either a reliability trigger or a price trigger from their utility system operator, load-serving entity, regional transmission organization (RTO)/Independent System Operator (ISO), or the demand response provider by lowering their power consumption." Nordic Power market also provided a definition for DR actions but in a more accurate way as: "a voluntary temporary adjustment of electricity demand as a response to a price signal or a reliability-based action."[6] One of the other definitions provided by the U.S. Department of Energy (DOE): "DR programs are the programs that improve the electricity consumption patterns of industrial, commercial, and residential customers so as to reduce peak loads and thereby achieve better prices as well as improved network reliability. To make the power demand more manageable, a DR program can change the pattern of electricity usage by reducing the peak load or shifting the consumption from the peak to the off-peak hours."[7]

DR can give very outstanding aspects, such as reliability, rapidity, accessibility, etc. In Ref. 8, the impact of DR programs on improving reliability is examined. Generally, DR programs are divided into two main categories (price-based DR and incentive-based DR) and several subcategories (Refs. 9–11) as shown in Fig. 1.

The critical peak pricing program is a price-based DR program during a specified critical time period, operated when high wholesale market prices or power system emergency conditions are observed.[12]

Compared to other pricing mechanisms in price-based DR programs, dynamic pricing [also known as real-time pricing (RTP)] has received more attention from market economists, as it creates a relationship between wholesale and retail sales.[13] RTP has been explained as a logical reaction to competition. In general, it is a solution for utilities to prepare their consumers with an actual market price which allows both to manage loads, decrease costs, and increase profit. It is also an effective solution for utilities to grow their competitiveness and hold their consumers.[14,15] Figure 2 reviews and categorizes the aims of implementation of RTP from the viewpoint of activists on the market.

Unlike time-of-use (TOU) pricing where electricity prices are pre-determined, in RTP end-use prices vary according to wholesale prices throughout the day. Economists believe that RTP-based DR action is the most straightforward and relevant tool for enabling active participation of consumers in competitive electricity markets. In a RTP-based scheme, the electricity prices differ from those of TOU because the latter assigns average electricity prices for each time period, while the former reflects the actual market price at the moment. Economists also believe that the use of time-varying prices leads to a greater economic efficiency in the electricity industry and markets. Figure 3 shows the consumer risk/reward in different pricing schemes. As can be seen in the figure, although other price-based schemes would yield lower risks for consumers compared to a RTP-based scheme, they also result in lower rewards and accordingly lower incentives for participation in DR programs which affect the market in a long-run operation.[16]

In Ref. 16, the long-term benefits of implementing a RTP scheme in an electricity market are discussed. Using simple simulations with actual parameters, the authors show that RTP has significant benefits, even when demand is less flexible against price change. In Ref. 17, an extensive review of utility experiences is presented about RTP programs. This review investigates 43 RTP programs presented in 2003. It has been eventuated that the most important motivation about these programs is consumer consent by preparing opportunities to maximize profitability.

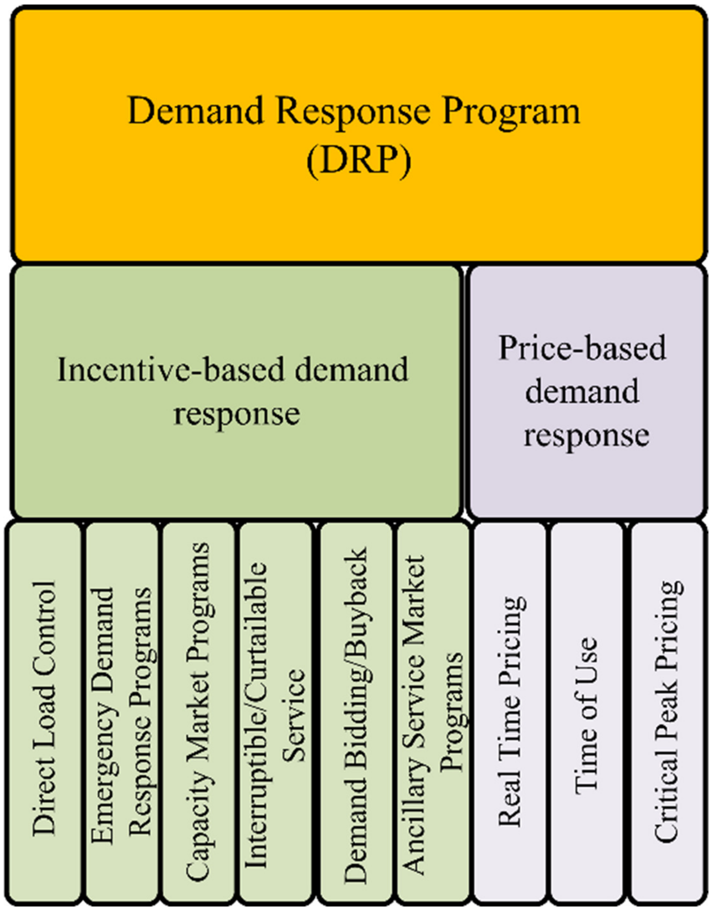

FIG. 1. Categories of DR programs.

A long-term survey of RTP usefulness is also carried out in Ref. 18 where it is shown that the benefits of using RTP are considerable even when the elasticity of demand is low.

In Ref. 19, a retailer company offers one of three pricing methods, RTP, TOU, and flat rate, and consumers adjust their consumption patterns with respect to prices to reduce their energy bills. The results obtained in this article verify the superiority of RTP. In Ref. 20, the impacts of RTP on prices, economic welfare, total demand, and peak demand hours in the Nordic power markets are investigated. The results show that the impacts of implementation of RTP are affirmative. In Refs. 21–26, the authors show that RTP programs can cause demands of peak time shift to other times and so decreases the cost of energy.

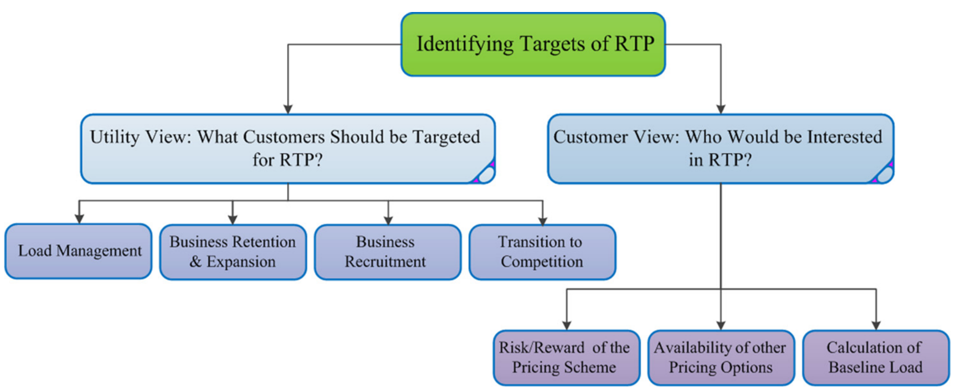

FIG. 2. Aims of RTP.

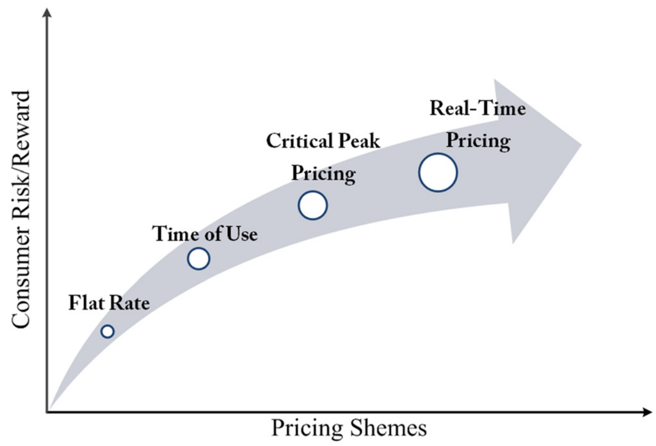

FIG. 3. Consumer risk/reward in different electricity pricing methods.

RTP can be implemented through two general procedures: Type-I—hour-ahead basis: announcing the real-time actual price of electricity, or Type-II—day-ahead basis: announcing the electricity price one day before.[27] In this paper, by developing the proposed method in Refs. 28 and 29 into the electricity market, we want to explore the uncertainties impacts have on consumption and savings. We consider a RTP-based market in which prices are announced as an hourly signal and the consumers are uncertain about the value of these prices in the coming hours. We utilize well-known economics theories and mathematical formulations to prove that the uncertainties of electricity prices can increase the consumers' willingness to participate in DR programs and aim to modify their consumption and savings. The main contribution would be to provide a reliable reference based on mathematical models showing that the use of dynamic pricing can lead to increased willingness of consumers to participate in DR programs which in turn improve the operation of liberalized electricity markets.

The organization of this paper is as follows. The theory of saving under uncertainty (SUT) is introduced in Sec. II. Afterward, Sec. III explains the mathematical formulation of this theory in association with RTP. Section IV presents a sensitivity analysis to study the effect of price uncertainty on consumer participation in DR programs. Section V presents numerical results and shows the validity of the proposed model. Finally, Sec. VI concludes the paper.

II. THEORY OF SAVING UNDER UNCERTAINTY (SUT)

Kenneth Ewart Boulding, who was nominated for the Nobel Prize in Economic Sciences, states that: "…*other things being equal, we should expect a man with a safe job to save less than a man with an uncertain job*."[30] From this statement, one can interpret that uncertainty about future earnings could lead to further savings. Extending this argument to the electricity market, it can be stated that: "*when a customer feels uncertain about electricity prices in coming hours, he tends to consume less to save more money for these hours*." Among all methods of electricity pricing, this concept is most compatible with RTP (Type-I), where price signals are announced on an hourly basis and the consumer has no information regarding future prices.

Considering such a scheme, let us assume that at the current hour the retailer sends price signal p_1 to the customer; however, the customer is uncertain about the value of the electricity price in the coming hours (signal p_2). In this respect, p_2 can be treated as a random variable between two values a and b

$$a \leq p_2 \leq b \tag{1}$$

in which a and b values can be set arbitrarily by the retailer according to the marginal cost and price caps. The greater $b - a$ means the larger the interval within which p_2 falls; in other words, signal p_2 can have more diverse values, and this implies a higher level of uncertainty.

In statistics and probability theory, the probability distribution function reflects the probability of a random variable being within a particular range of values.[31] With regards to this, we can consider signal p_2 as a random variable with continuous uniform distribution between the two values a and b. Thus, the probability density function of this parameter can be assumed as follows:

$$f(p_2) = \begin{cases} \dfrac{1}{b-a}; & b \le p_2 \le a \\ 0; & p_2 < a \;\; or \;\; p_2 > b. \end{cases} \tag{2}$$

Figure 4 illustrates such a continuous uniform distribution.

This uniform distribution function has the following mean and variance:

$$E(p_2) = \mu = \frac{b+a}{2}, \tag{3}$$

$$Var(p_2) = \sigma^2 = \frac{(b-a)^2}{12}, \tag{4}$$

$$Std(p_2) = \sigma = \frac{(b-a)}{2\sqrt{3}}. \tag{5}$$

Standard deviation (*Std*) can also be used to determine the level of confidence in the statistical analysis.[32] It also has a direct relationship with the confidence coefficient, i.e., as *Std* increases, so does the uncertainty in a given stochastic signal such as the price signal. It can be also understood from Eq. (5) that *Std* is directly related to *b*–*a*, which implies that the greater *b*–*a*, the higher would be the level of uncertainty.

Considering the above-mentioned definitions, we must now prove that "when *Std* is growing, the customer tends to consume less to save more money for these hours." To this end, by using mathematical models and techniques we will try to prove this argument, and if successful, we will show how RTP increases the consumers' willingness to participate in DR programs and accordingly we will prove Bounding's theory for electricity markets.

III. SUT FORMULATION FOR ELECTRICITY MARKET

Assume that a customer allocates a budget of B \$ to the electricity bill a day ahead, and receives the price signal on an hourly basis. At the current hour, having received the price signal $p_{1,}$ the customer needs N_1 \$ to cover his current consumption $n_{1,}$ which leaves him with N_2 \$ in the coming hours of the day

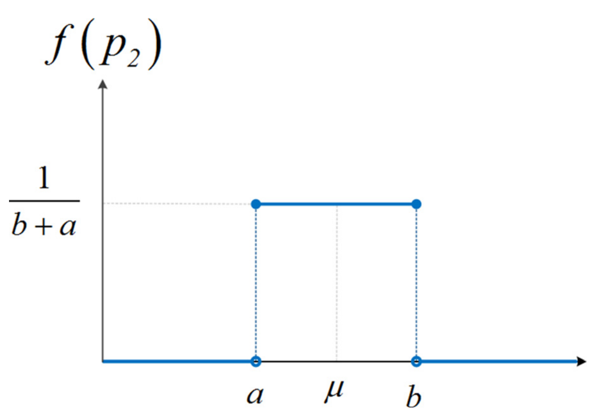

FIG. 4. Continuous uniform distribution.

$$\begin{aligned} B &= N_1 + N_2, \\ N_1 &= n_1 p_1, \\ N_2 &= n_2 p_2, \end{aligned} \tag{6}$$

where n_1 and n_2 are the amounts of electricity that can be purchased with N_1 \$ and N_2 \$, respectively. Now by extending the Boulding's theory to the electricity market it is demonstrated how the presence of uncertainty in electricity price (p_2) would incentivize the customer to consume less and to save more money for the coming hours.

Suppose that due to the price uncertainty, a customer saves S_1 \$ of his previous budget N_1 for the coming hours. Thus, adjusting this budget would yield

$$D_1 = N_1 - S_1; \quad S_1 \geq 0, \tag{7}$$

$$D_2 = N_2 + S_1, \tag{8}$$

where D_1 is the adjusted budget of the current hour and D_2 is the adjusted budget of the coming hours. Considering the price signals p_1 and p_2, the electricity consumption will be

$$\begin{aligned} D_1 &= d_1 p_1, \\ D_2 &= d_2 p_2, \end{aligned} \tag{9}$$

where d_1 and d_2 are the amount of electricity that can be purchased now and in the future after the budget adjustment, respectively. To prove the Bounding's theory for the electricity market, now it must be shown that S_1 varies with the amount of uncertainty in price signals (p_2) of the coming hours and accordingly find the right answers to the following questions: "*Does increasing uncertainty in price signal have any effect on* S_1?" and if yes, "*what is the magnitude and direction of this effect*?"

By substituting Eq. (7) into Eq. (8) and considering Eq. (6), it can be stated that

$$D_2 = N_2 + S_1 = N_2 + (N_1 - D_1) = n_2 p_2 + (n_1 p_1 - d_1 p_1). \tag{10}$$

Thus, the utility function U (D_1, D_2) for the customer will be

$$\begin{aligned} U(D_1, D_2) &= U(D_1, N_2 + (N_1 - D_1)) = U(d_1 p_1, n_1 p_1 + n_2 p_2 - d_1 p_1), \\ B &= D_1 + D_2, \end{aligned} \tag{11}$$

where B denotes the total budget allocated by the customer to his electricity bill.

In this article, we have explained the real-time price according to the probability distribution function. However, we used the utility function to explain the probability of the consumer's presence in the formulations. As we know, the degree of probability of the consumer's presence is the same as the concept of elasticity.[11] In economics, elasticity refers to the degree to which consumers change their demand in response to price. In other words, elasticity determines the extent of the consumer's presence. There are many functions that can be selected to express the utility function of consumers. But in this article, we used the Cobb-Douglas utility function which is one of the most famous utility functions that economists extensively use in macroeconomics. The general form of this function is shown below[33,34]

$$\begin{aligned} U(D_1, D_2) &= \left(D_1^{\alpha}\right) \cdot \left(D_2^{1-\alpha}\right); \quad 0 < \alpha < 1, \\ B &= D_1 + D_2. \end{aligned} \tag{12}$$

Parameter "α" (elasticity) determines the consumer's presence in the DR program. So here we determine the probability of the consumer's presence with this parameter and then we can show the different scenarios of the consumer's presence with distinct probabilities by the help of different values of this parameter.

In this paper, we assume that $\alpha = \frac{1}{2}$, thus

$$U(D_1, D_2) = \left(D_1^{1/2}\right) \cdot \left(D_2^{1/2}\right) = (d_1 p_1)^{1/2} \times (n_1 p_1 + n_2 p_2 - d_1 p_1)^{1/2}. \tag{13}$$

Figure 5 illustrates the distribution of the Cobb-Douglas utility function.

The objective in the next step is to develop a model of choice behavior under uncertainty. We start with the von Neumann-Morgenstern expected utility model, which is the workhorse of modern economics.[35,36] Based on this model the expected utility can be expressed as follows:

$$E(U) = \int U(D_1, D_2) f(p_2)\, dp_2. \tag{14}$$

Substituting Eqs. (2) and (13) into Eq. (14)

$$\begin{aligned} E(U) &= \int U(D_1, D_2) f(p_2)\, dp_2 = \frac{(d_1 p_1)^{1/2}}{b-a} \int_a^b (n_2 p_2 + n_1 p_1 - d_1 p_1)^{1/2} dp_2, \\ &= \frac{2 (d_1 p_1)^{1/2}}{3 n_2 (b-a)} \left[(b n_2 + n_1 p_1 - d_1 p_1)^{3/2} - (a n_2 + n_1 p_1 - d_1 p_1)^{3/2} \right], \\ &= \frac{2 D_1^{1/2}}{3 n_2 (b-a)} \left[(b n_2 + N_1 - D_1)^{3/2} - (a n_2 + N_1 - D_1)^{3/2} \right]. \end{aligned} \tag{15}$$

To calculate the maximum value, the derivative should be zero and the second derivative should be negative, thus the maximum value in terms of D_1 must satisfy the following two conditions:[37]

$$\frac{dE(U)}{dD_1} = 0 \quad \text{and} \quad \frac{d^2 E(U)}{d^2 D_1} < 0. \tag{16}$$

Therefore

$$\begin{aligned} \frac{dE(U)}{dD_1} &= (b n_2 + (N_1 - D_1))^{3/2} - (a n_2 + (N_1 - D_1))^{3/2} \\ &\quad - 3 D_1 \left((b n_2 + (N_1 - D_1))^{1/2} - (a n_2 + (N_1 - D_1))^{1/2} \right) = 0. \end{aligned} \tag{17}$$

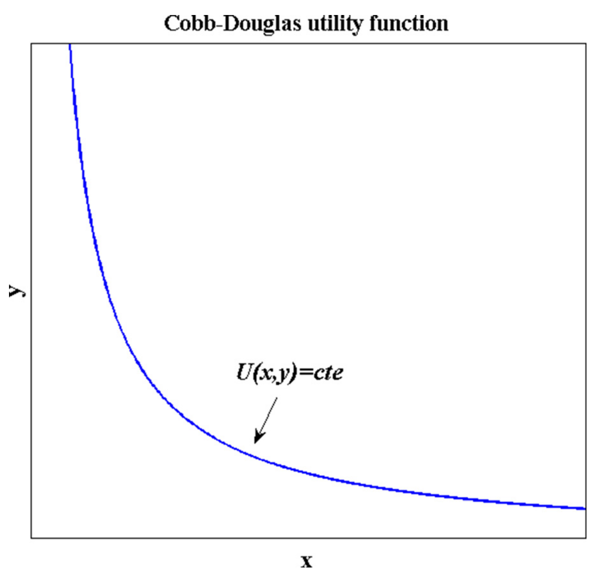

FIG. 5. Cobb-Douglas utility function for $\alpha = \frac{1}{2}$.

Solving the above equation gives two solutions

$$\begin{cases} (1) \Rightarrow \; a = b \\ (2) \; \Rightarrow bn_2 + an_2 + 2((N_1 - D_1)) - 3D_1 = -(bn_2 + (N_1 - D_1))^{1/2}(an_2 + (N_1 - D_1))^{1/2}. \end{cases} \tag{18}$$

The first solution is unacceptable. For the second solution, we raise both sides of the equation to the second power and sort it in terms of D_1. Now, according to the second derivative condition for the maximum of the utility function, the optimal solution which is defined as the amount of money that customer spends on electricity (based on the described price signal) will be

$$D_1 = \frac{18 \times \left(\frac{bn_2 + an_2}{2} + N_1\right) + 6 \times \sqrt{\left(\frac{bn_2 + an_2}{2} + N_1\right)^2 - \left(\frac{8(bn_2 - an_2)^2}{12}\right)}}{48}. \tag{19}$$

Substituting Eqs. (3) and (4) into Eq. (19) gives

$$D_1 = \frac{18 \times (\mu n_2 + N_1) + 6 \times \sqrt{(\mu n_2 + N_1)^2 - 8n_2^2\sigma^2}}{48}. \tag{20}$$

After simplification, we have

$$\begin{gathered} D_1 = \frac{3}{8}(\mu n_2 + N_1) + \frac{1}{8}\sqrt{\left(\mu n_2 + N_1 - 2\sqrt{2}n_2\sigma\right) \cdot \left(\mu n_2 + N_1 + 2\sqrt{2}n_2\sigma\right)}, \\ d_1 = \frac{D_1}{p_1}. \end{gathered} \tag{21}$$

As mentioned, σ is the *Std* or the square root of the variance. The last equation can be rewritten as follows:

$$\begin{gathered} S_1 = \frac{5}{8}N_1 - \frac{3}{8}\mu n_2 - \frac{1}{8}\sqrt{\left(\mu n_2 + N_1 - 2\sqrt{2}\sigma n_2\right) \cdot \left(\mu n_2 + N_1 + 2\sqrt{2}\sigma n_2\right)} \;; \quad \sigma \in \left[0 \;,\; \frac{\mu n_2 + N_1}{2\sqrt{2}n_2}\right], \\ s_1 = \frac{S_1}{p_1}. \end{gathered} \tag{22}$$

IV. SENSITIVITY ANALYSIS

This section describes the results of a sensitivity analysis to evaluate the effect of price uncertainty on consumer participation in DR programs. In sensitivity analysis, we check the effect of a change in one independent variable on the dependent variable, assuming that all other variables and conditions are known and constant.[38] Here, σ is treated as the independent variable and we study the effect of a change in this variable on other dependent variables D_1 and S_1 in Eqs. (21) and (22), respectively.

A. Sensitivity analysis of saving

In the first sensitivity analysis, we study the effect of σ on the value of S_1. By increasing the value of σ and consequently increasing the uncertainty of future prices, it is expected to increase the value of saving S_1. The sensitivity analysis result depicted in Fig. 6 confirms the validity of this assumption.

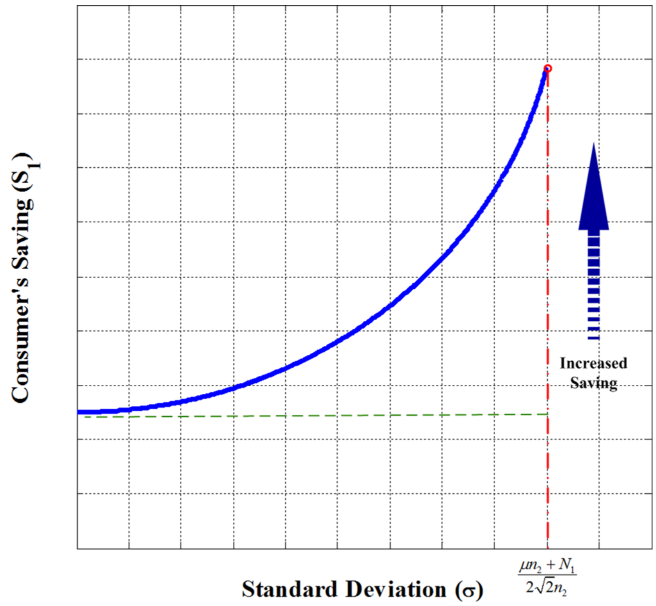

FIG. 6. Changes in saving as the result of an increase in *Std*.

B. Sensitivity analysis of consumption

In the second sensitivity analysis, the effect of σ on the value of D_1 is investigated. Here, we expect that increasing the value of standard deviation σ can reduce the consumption, and the results of sensitivity analysis verify this statement (see Fig. 7).

As can be seen from the results of both sensitivity analyses, for uncertainties of higher than a certain threshold $\{(\mu n_2 + N_1)/(2\sqrt{2}\,n_2)\}$ there is no feasible solution, meaning that the uncertainty is so high that the consumer's decision-making process ends at a point of cessation.

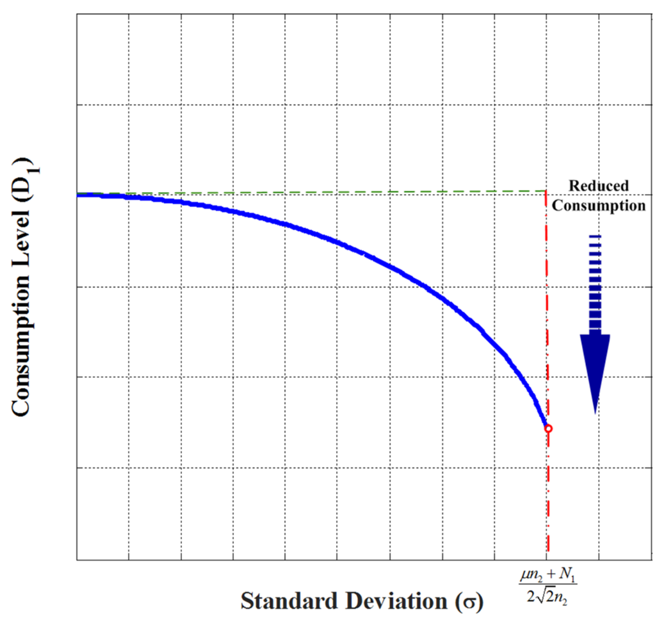

FIG. 7. Changes in consumption as the result of an increase in σ.

TABLE I. Consumer's data for the current hour.

	Current hour			
Data for consumer	Budget B ($)	p_1 (cents per kWh)	p_2 (cents per kWh)	n_1 (kWh)
	16.42	8	16	102.6650

V. CASE STUDY

Table I shows the data used for the case study that is extracted from Ref. 39. This case study deals with implementation of the TOU DR program for a sample of aggregated residential customers in the Northwestern Energy utility. In this case study, each customer has a fixed consumption and it is assumed that diurnal hours are divided into two periods: (1) off-peak time and (2) peak time. It is also assumed that each time period has its own fixed and unique price as shown in Table I.

In this paper, we apply the RTP scheme instead of the TOU scheme. According to this scheme, it is assumed that electricity price is uncertain in the coming hours but its average value would be equal to the price level in the TOU scheme (e.g., 16 cents per kWh). By doing this, we want to show how price uncertainty could affect the consumption behavior over time, although the average price is constant.

To form the probability distribution function, values of a and b are chosen in such a way that the average electricity price for the coming hours is equals to 0.16 \$. Thus, for the selected a and b: $\mu = (b + a)/2 = 0.16\,\$$. As Table II shows, although selecting the proper values for a and b results in a fixed average price μ for the coming hours, the value of $(b - a)$ would be different. As mentioned earlier, this difference in value is in fact the length of the interval within which a future price signal can vary. The greater the length of this interval, the more diverse the prices can be, which means the greater uncertainty in prices (and hence greater *Std* and so increased risk).

As can be seen from the numerical results of Table II, when uncertainty (*Std*) increases, user's consumption level decreases which directly implies an increase in user's saving. It can be further observed that there is a significant difference in user's saving among TOU- and

TABLE II. Changes in electricity saving.

Scenario #	DR program	a	b	μ	b-a	*Std* (σ)	Saving (cents)	Consumption (kWh)
1	TOU	0.16	0.16	0.16	0	0	0	102.6650
2	RTP	0.15	0.17	0.16	0.02	0.0058	0.5872	102.5916
3	RTP	0.14	0.18	0.16	0.04	0.0115	1.3912	102.4911
4	RTP	0.13	0.19	0.16	0.06	0.0173	2.7376	102.3228
5	RTP	0.12	0.20	0.16	0.08	0.0231	4.6384	102.0852
6	RTP	0.11	0.21	0.16	0.10	0.0289	7.108	101.7765
7	RTP	0.10	0.22	0.16	0.12	0.0346	10.1696	101.3938
8	RTP	0.09	0.23	0.16	0.14	0.0404	13.8512	100.9336
9	RTP	0.08	0.24	0.16	0.16	0.0462	18.1888	100.3914
10	RTP	0.07	0.25	0.16	0.18	0.0519	23.2288	99.7614
11	RTP	0.06	0.26	0.16	0.20	0.0577	29.0328	99.0359
12	RTP	0.05	0.27	0.16	0.22	0.0635	35.6776	98.2053
13	RTP	0.04	0.28	0.16	0.24	0.0692	43.268	97.2565
14	RTP	0.03	0.29	0.16	0.26	0.0750	51.9424	96.1722
15	RTP	0.02	0.30	0.16	0.28	0.0808	61.8976	94.9278
16	RTP	0.01	0.31	0.16	0.30	0.0866	73.4232	93.4871
17	RTP	0	0.32	0.16	0.32	0.0924	86.9768	91.7929

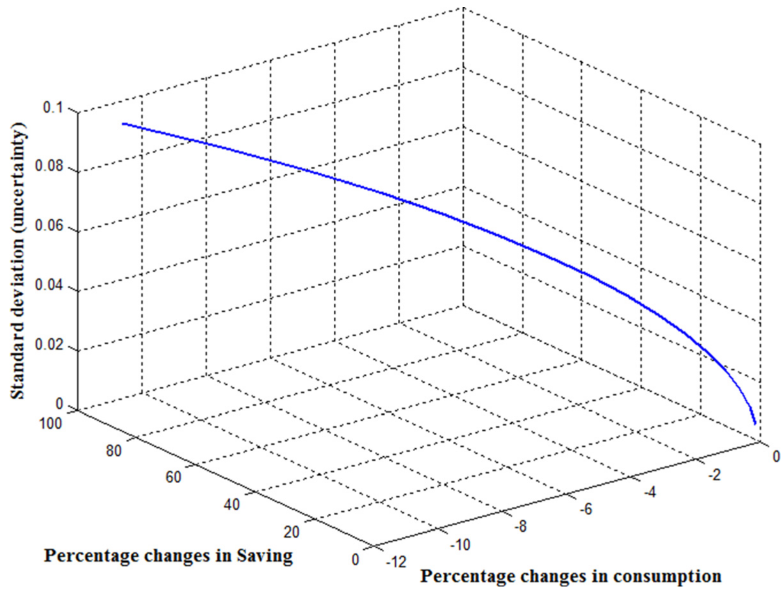

FIG. 8. Changes in consumption and savings versus standard deviation.

RTP-based DR actions, which highlights the fact that "*where dynamic pricing is applicable, it would be a worthwhile effort to deploy RTP-based DR programs*."

To get a better insight into the relationship between the aforementioned variables (*Std*, user's saving, and consumption behavior), simulation results for relative changes in consumption and saving levels as a function of *Std* are shown in Fig. 8. Here the term "relativity" is used to describe the quantitative changes of dependent variables under different operating conditions (i.e., dynamic pricing condition compared to a TOU-based scheme). It is clearly understood from the results that the consumption level decreases relatively as *Std* increases (which implies higher risks), which in turn increases the user's saving, as expected. In other words, as the uncertainty in the future energy prices increases, consumers tend to participate more in DR programs and their contribution level is further increased by utilizing the RTP mechanism (compared to a TOU-based scheme).

Figure 9 demonstrates the effect of an average electricity price and its uncertainty level on consumer's energy saving. As it is observed, with a constant *Std*, by increasing average

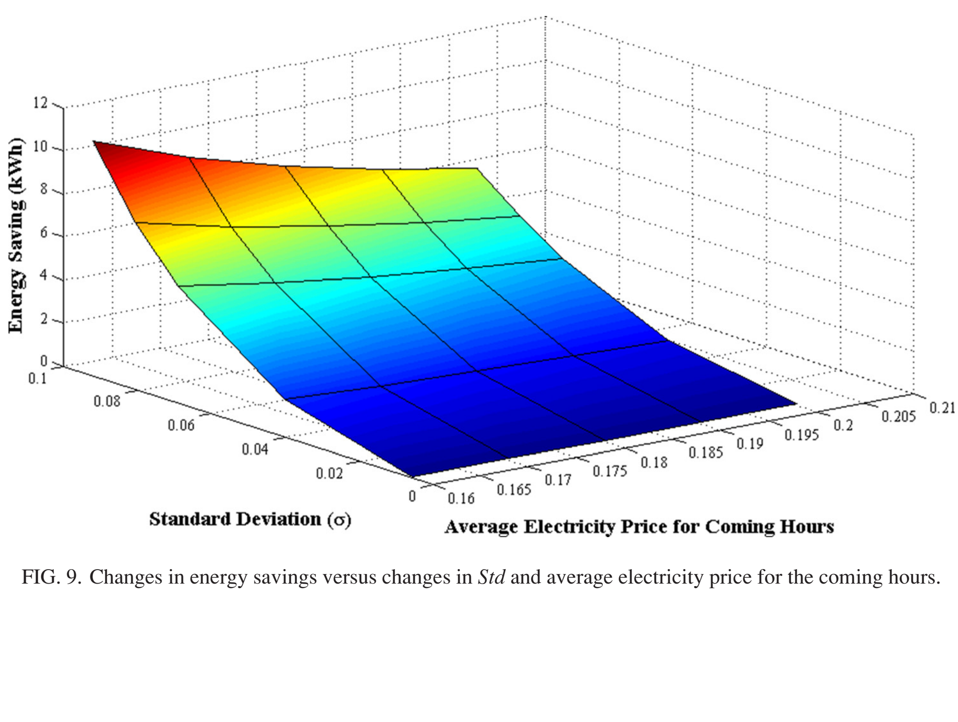

FIG. 9. Changes in energy savings versus changes in *Std* and average electricity price for the coming hours.

electricity price for the coming hours, the customer feels that prices are relatively good and he is better off consuming electricity now than later, hence the amount of savings decreases.

It is noteworthy to mention that one of the most serious issues that consumers have uttered in the RTP programs is that they are at continuous "risk/reward" due to price variations unlike flat rate and partly TOU programs. The "risk" is deemed to be that a consumer consumes large amounts of energy regardless of price changes, so he may receive an electricity bill larger than his budget. On the other hand, this consumer can alter his electricity consumption pattern according to price variations to achieve "rewards."

VI. CONCLUSION

In this paper, it was mathematically proven and demonstrated that an electricity market based on a real-time pricing (RTP) scheme would increase the consumers' willingness to participate in demand response (DR) programs. By using the theory of saving under uncertainty, it was also shown that increasing the uncertainty of price information would reduce the actual electricity consumption and accordingly increase the electricity savings for consumers. In other words, compared to other price-based mechanisms, implementing the RTP scheme in a given liberalized electricity market would increase the uncertainty in electricity prices for the coming hours and subsequently decrease the electricity consumption by enabling DR actions. However, it should be noted that implementing a RTP-based DR program increases the risk-level at the demand-side so much that any negligence on the part of the consumer could lead to a significant increase in his electricity bill. Thus, to effectively set up such a scheme which benefits both supply and demand sides and improves the market operation, it is crucial to have proper communication infrastructures as well as adequate access to smart appliances such as smart washing machines, dishwashers, thermostats, etc., to enable the customer to adapt to hourly changes in the electricity prices.

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