Designing Incentive-based Demand Response Program for Minimizing Financial Risk of Retailer during Peak Period

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Abstract:

In this paper, a customer incentive scheme is proposed for retailers to build an effective demand response program over the peak demand period to minimize the financial risk. Firstly, an objective function is formulated based on the market operation and an optimal incentive price is derived from this objective function. Secondly, the incentive price is employed as a part of an incentive scheme to encourage customers to reduce their electricity demand to a certain level during peak hours. Two typical customer response scenarios are studied to investigate the impact of customer response sensitivity on the loss of utilities' and customers' profit. Finally, a dataset for the state of New South Wales, Australia is employed as a case study to examine the effectiveness of the proposed scheme. The obtained results show that the proposed scheme can help to improve the elasticity of demand significantly thereby reducing the associated financial risk greatly. Moreover, the proposed scheme allows customers to get involved voluntarily and maximize their profits with minimum reduction of their comfort levels.

Keywords: Customer incentive scheme, demand elasticity, demand response, electricity price spikes, financial risk.

Journal of Iranian Association of Electrical and Electronics Engineers - Vol.15- No.4- Winter 2018

Submission date: 21, 11, 2017

Acceptance date: 07, 11, 2017

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1. Introduction

Electric power system is operated based on a strict, simultaneous balance between demand and generation. To match peak demand following seasonal and daily fluctuations, and to ensure reliable operation of the electric power system, a substantial number of high marginal cost generators are upheld to serve the requisite demand in a short term period [1]. Also, in order to serve short term peak load, huge investments need to be made in transmission and distribution networks [2]. This utilization of assets contributes to one of the biggest portions of the electricity price. In addition, generators serving peak load demand may use fossil fuels such as gas and diesel as primary energy sources, which may be detrimental to the environment. Furthermore, with constraints related to intermittency and uncertainty of generation, peak demand may surpass the capacity of all available power plants together, and this may influence the security of power system. In order to tackle these issues, demand response (DR) program can be considered as an effective solution [3]. DR can offer not only a cost-effective alternative to meet the peak and/or occasional demand spikes but also a mean to avoid system emergencies.

Recently, numerous research studies have been carried out on the applicability of DR schemes [4], [5]. In general, DR can be categorized into time-based DR and incentive-based DR [6]. Time-based DR refers to reduction in customer demand for price rise signals [7], and it includes two popular strategies which are time of use (TOU) pricing [8] and real-time pricing [9]. In the TOU scheme, electricity price is set to be significantly higher during peak periods thereby motivating the consumers to shift the demand from a peak period to off-peak period. The shifting process can be optimized using various methods such as heuristic approach [10], stochastic security constrained unit commitment method [11], or game theory [12]. These optimization algorithms help to shift demand effectively ensuring continuity of supply to the load. However, simply shifting loads to certain off-peak hours may not have much influence on the financial benefit to utilities and customers [13]. Furthermore, it could eventuate into peak loading condition at a new time period, which invalidates the load shifting strategy [14], [15]. Real-time pricing, with utilization of the automatic metering infrastructure, can help solve above-mentioned problem [16]. The real-time pricing may enhance competitiveness in the market and encourage more bidding activities in the market [17], [18]. Furthermore, real-time pricing scheme can consider the participation of new source like electric vehicle in the bidding process [19], [20]. However, the real-time pricing scheme may cause more volatility to the market operation since small changes in price signal may result into massive changes to customer payments.

Unlike time-based DR, incentive-based DR refers to customers receiving payments or preferential prices from reducing electricity usage during periods wherein system experiences stress in meeting the customer demand. One of the popular incentive-based DR programs is direct load control [21] under which utility or system operator remotely shuts down or cycles customers' electrical equipment on short notice. In order to improve the performance of DR, cooperation between loads can be integrated via multiple layers of control strategy [22], [23]. Although customers' appliances can be turned off a number of times per year or season, the DR scheme proposed in [22] enforces customers to turn off appliances on request, which may not be a convenient option for customers. Recently in [24], a coupon incentive scheme was introduced to encourage small scale customers in reducing the load in peak price period. This scheme is operated based on the voluntary basis and customers can earn coupon credit for reducing the demand when system needs, thus it is more flexible for the customers to decide whether to participate or not. However, the consideration of customer response is limited by linear response assumption thus it may not be sufficient in evaluating the influence of customers' types on the effectiveness of the proposed scheme.

In this paper, a customer incentive scheme is proposed for building an effective incentive-based DR program. In this program, an incentive scheme is proposed with an incentive price to encourage customers to reduce the electricity demand quantity to a certain level when price spikes are detected. An optimization problem is formulated to minimize utilities' financial losses based on changing the offered incentive price. Linear approach was employed to solve the problem and the optimum incentive price is determined at a point where utility loss is at minimum level. Furthermore, it is revealed that customers' responses do have strong impacts on the optimization process of the proposed scheme. Consequently, two typical customers' response scenarios which are linear and restricted responses are investigated. The main findings of the paper and their significance are listed below:

- A customer reward-based demand response strategy is proposed to improve the elasticity of electricity demand.
- An optimization problem is formulated to minimize the financial losses incurred by the utilities with the aid of a newly proposed customer incentive scheme.
- Two typical customers' response scenarios; namely linear response and restricted response are investigated.
- For a higher sensitivity of customers' response, it is found that the optimum incentive price and utility losses are lower.

The paper is organized as follows. Section 2 presents the problem description relating to the inefficiency of peak load demand and uncertainty of renewable generation. Section 3 introduces a customer incentive scheme for developing an effective DR program. Section 4 provides experimental results and discussions. Section 5 highlights the concluding remarks of the paper.

2. Problem Description

Current electricity market may suffer from two main challenges in utilizing the generation units. The first one is reserving a number of expensive generators to match the peak load in very short period each year. Since these generators are only operated occasionally, they are inefficient and they impose high electricity price to customers' bill. The second challenge is the increasing uncertainty in generation capacity when more intermittent renewable energy sources such as wind power participate in the electricity market. This uncertainty can cause sudden reduction of generation and lead to spikes in electricity prices. Accordingly, it creates increasing financial risks for utilities.

2.1. Inefficient Peak Load Period

To match peak demand following seasonal and daily fluctuations, and to ensure reliable operation of the electric power system, utilities are forced to maintain a substantial amount of underutilized power capacity [1]. The generation serving in this period is highly marginal cost generators [25]. In addition, transmission and distribution assets need to be built to meet peak demands. Therefore, high peak demands contribute to one of the biggest portions of electricity price [2]. For illustration, the aggregated demand for New South Wales (NSW), Australia which is acquired from Australian energy market operators (AEMO) [26] for year 2015 is presented in Fig. 1.

It can be seen from Fig. 1 that about 20% of capacity is used to serve peak load demand which contributes to only 5% time of operation in a year. In order to maintain the balance between demand and generation, high marginal operating cost generators are needed to fulfil the need of peak demand. For example, in order to supply to peak demand in summer season, Australian gas light company has proposed to build a new gas power plant in South Australia (SA) [27]. On the one hand, the plan helps to handle the peak load, and avoid the blackout during peak demand. On the other hand, operation of these generators is uneconomic because they usually have extremely high marginal operating cost. In addition, they are operated using fossil fuel so they are not friendly to ecosystem. As a result, deployment of such generators causes reduction in economic benefit and brings more impairment to environment.

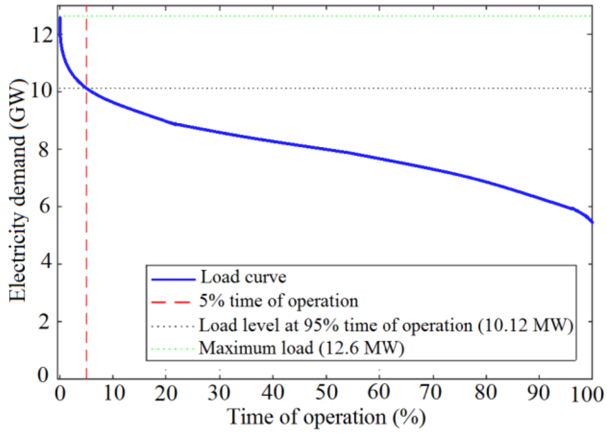

Fig. 1. Aggregated demand at different serving duration in 2015 for NSW, Australia

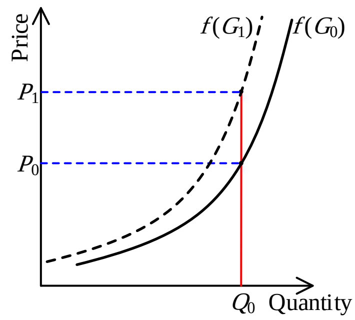

Fig. 2. Price jump due to reduction of low marginal cost generation

2.2. Generation Uncertainty

The participation of renewable energy resources in generation mix is boosted dramatically in recent years with different programs and agreements among countries around the world. Such a scenario is expected to make significant contribution in decreasing greenhouse gas emissions originating from fossil-fueled power plants. However, wind generators introduce more uncertainty in the power system due to inherent intermittency of wind power. This uncertainty could cause sudden reduction in generation capacity and thus lead to a huge shift of generation bidding curve. Also, it creates a huge jump of electricity price in the spot market. The influence of a wind generation is illustrated in Fig. 2.

It can be seen from Fig. 2 that at the normal condition, a quantity Q_0 , which is required by customers, is bought by utilities at a spot price P_0 , which is determined by the matching point between quantity Q_0 and generation represented by the bidding curve $f(G_0)$. If there is a sudden reduction in cheap generation (*i.e.*, wind generation), the bidding curve shifts to the left with the new position represented by $f(G_1)$. If the demand remains at Q_0, the spot price jumps from the normal price P_0 to a spike value of P_1 which may be extremely higher than the retail price. As a result, utilities may suffer from short-term financial loss when it is forced to buy electricity at higher price and sell at lower price to maintain the security of the system within the occurrence of spikes. Furthermore, sudden reduction of wind generation can lead to lack of generation in peak demand, thus cause serious problem that may lead to system blackout. For example, the occurrence of partial load shedding blackout in SA on 8th of February 2017 [28] is due to lack of generation when load demand was peaking on a hot day but wind did not flow and thus wind generators could not produce electricity.

2.3. Demand Elasticity Opportunity

Peak load causes more ineffective investment on generators and network infrastructure, which consequently boost the electricity price at the retail level. Furthermore, the renewable generation such as wind power may not be coincident with peak load, so it cannot solve the problem. On top of that it may introduce more uncertainty into the market thus pushes utilities to expose to more financial risk, and impacts the security of the power system. In order to tackle the above-mentioned issues, elasticity of demand should be improved. When demand can be adapted to cope with short fall of generation, the balance of the system can be maintained healthily, and market can be operated efficiently. For example, the financial benefit for utilities arising from demand elasticity is given in Fig. 3.

The benefit of demand response which is presented in Fig. 3 is explained as follows. In the normal operation, generation bidding can be considered as a function of price $G_1=g_1(P)$, and the quantity of demand is at Q_0. Consequently, the utilities buy Q_0 at a spot price P_{s0} and sell to customers at a retail price P_r, which is higher than P_{s0}, and earn profit from this trading process. When there is a sudden reduction in cheap generation, the bidding curve is shifted to a new position, which is represented by $G_2=g_2(P)$. This shift of bidding curve cause the spot price to change from P_{s0} to P_{s1}, which is much higher than the fixed retail price P_r. As a result, utilities are exposed to financial risk with a huge trading loss. In order to reduce this loss, utilities will somehow convince customers to reduce the demand ΔQ from Q_0 to Q_1. With this demand reduction, the spot price reduces from P_{s1} to P_{s2}, thus it decreases the trading loss for utilities.

3. Customer Incentive Scheme

The DR algorithm proposed in this study is based on a customer incentive scheme which allows utilities to communicate with customers for an agreement on reducing demand to mitigate spot price spikes.

3.1. Conceptual Design

Utilities buy electricity from a spot market and sell it to customers in a retail market. In other words, utilities are involved into two markets, which are the spot market and retail market. The participation of one utility can be briefly described as in Fig. 4.

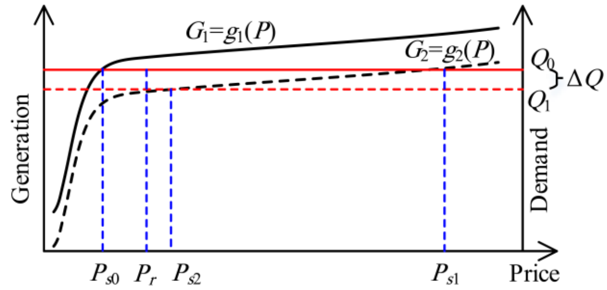

Fig. 3. Demand elasticity to reduce spike prices

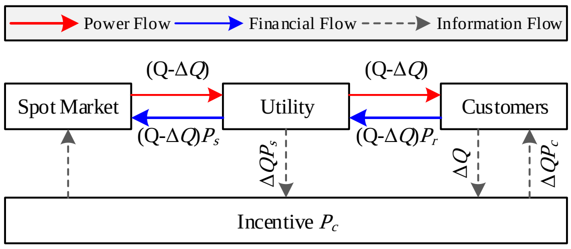

Fig. 4. Conceptual diagram of proposed customer incentive scheme

The concept of the proposed customer incentive scheme is presented as follows. In the normal condition, the reduction of quantity ΔQ is zero, thus utilities buy a quantity Q from spot market at a spot price P_s and sell it to the customers at a retail price P_r which is higher than P_s. From this trading process, utilities earn a trading profit which can be presented as follows (assuming the demand and price remain the same for one hour, so the profit is for one hour energy consumption):

$$\text{Profit} = Q \times (P_r - P_s) \tag{1}$$

In a critical market condition such as peak load demand or sudden reduction of cheap energy sources, the spot price P_s suddenly increases to a spike value, which is higher than the retail price P_r. As a result, utilities may suffer from negative profit or loss: {Loss = –Profit = $Q\times(P_s–P_r)$}. It is assumed that for the dependence of spot price P_s on demand quantity Q in this incident following a given function $P_s= f(Q)$, the trading loss for utilities is represented as follows:

$$\text{Loss} = Q \times (f(Q) - P_r) \tag{2}$$

In order to reduce this loss, utilities introduce a customer incentive scheme (which can be described as an additional block "incentive" in Fig. 4). In this scheme, utilities encourage customers to reduce a demand quantity ΔQ by paying them an incentive price P_c for each unit of quantity reduction. This reduction reduces the trading demand quantity between spot market and retail market from Q to $(Q- \Delta Q)$, thus moderates the spot price from $f(Q)$ to $f(Q- \Delta Q)$. The new total financial losses for utilities can be represented as follows:

$$\text{Loss} = (Q - \Delta Q) \times (f(Q - \Delta Q) - P_r) + \Delta Q \times P_c \tag{3}$$

The new total financial loss in (3) includes two main components, which are trading loss $(Q-\Delta Q)\times(f(Q-\Delta Q)-P_r)$ and incentive payments $\Delta Q\times P_c$, which utilities have to pay to customers to encourage them to reduce demand quantity ΔQ. By changing the value of incentive price P_c, utilities can estimate the new loss and minimize the total financial loss accordingly.

3.2. Algorithm and Optimization

The algorithm of the proposed scheme can be summarized as follows. Utilities continuously monitor the conditions of the electricity market to detect price spikes. If a spike incident is detected, utilities trigger a customer incentive scheme with an incentive price P_c to encourage customers to reduce electricity quantity ΔQ. Accordingly, the total financial loss for utilities may vary with the incentive price they offer. Utilities may change the value of P_c until their total financial loss is minimized. The summary of the proposed algorithm is given in Fig. 5.

It can be seen from the above algorithm that the aim of the scheme is to minimize the total financial losses for utilities by changing incentive price P_c. Therefore, the objective function can be described as follows:

$$\min_{P_c}: \left\{ (Q-\Delta Q)\times\left(f\,(Q-\Delta Q)-P_r\right)+\Delta Q\times P_c \right\} \quad (4)$$

$$\text{subject to} \begin{cases} 0 \le \Delta Q \le \Delta Q_{\max} \\ P_c \ge 0 \\ 0 < f\,(Q-\Delta Q) \le f\,(Q) \end{cases} \quad (5)$$

The first constraint means that the reduction is not negative, and it has an upper limit depending on actual consumption of customers. In the second constraint, the incentive price should be greater than or equal to zero so that customers are encouraged to participate. The last constraint implies that the spot price after demand reduction is positive and it is smaller than the original price spike.

The success of the incentive program is heavily dependent the estimation of the function representing the relationship between spot price and electricity demand quantity. This relationship can be estimated from the bidding information of generator (e.g. presented in Fig. 7). In the context of this paper, the relationship is assumed to follow an exponential equation (uplift behavior), inferred from [29], which is given below:

$$f\,(\xi)=a_0+a_1\times\xi+\alpha_0\times e^{(\alpha_1\times(\xi-\xi_0))} \quad (6)$$

where, a_0, a_1, α_0, α_1 are constant. ζ is the level of electricity demand. $f(.)$ represents the function of the electricity spot price.

Furthermore, it can be seen from the conceptual operation of the proposed customer scheme in Fig. 4 that the customers' response is crucial to the operation of the proposed scheme. Customer response can be investigated using different scenarios as discussed in the following subsection.

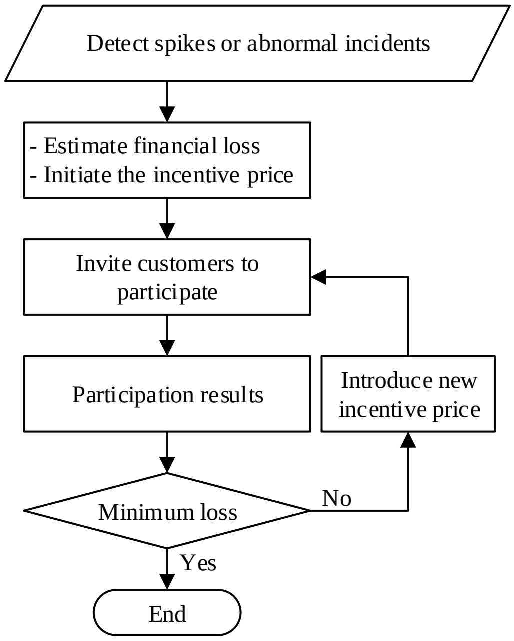

Fig. 5. Demand elasticity to reduce price spikes

3.3. Customer Response Scenarios

In a customer incentive scheme, it is crucial to estimate the response behavior of customers to an incentive payment. The estimation can be achieved using a stochastic model [30], and it may be dependent on types of load and its location, etc. However, the actual data for this response is not available, thus the response is assumed to follow some predefined function. In this paper, two typical responses which are linear response and restricted response are considered.

3.3.1. Linear response

The response of customers can be simplified using a linear relationship representation as in [24]. With this assumption, the response is linearly proportional to the incentive payment and it can be modelled as follows:

$$\Delta Q = k_r \times Q \times P_c \quad (7)$$

where, ΔQ is the response of customers Q, is the quantity of demand, P_c is incentive price and k_r is a non-negative constant indicating the response slope which represents the sensitivity of the customers' response and reflects customers groups.

It is noted in (7) that, $0 \le \Delta Q \le Q$ and $P_c \ge 0$ are applied. At a specific demand quantity from one customer group k_r, the response of customers is linearly dependent on the offered incentive price P_c.

3.3.2. Restricted response

From the customers' perspective, the reduction of an electricity quantity may influence their outcome product (or customer's comfort). Consequently, the response of customers may be restricted to the outcome product achievement. In this subsection, an elaborated case of customers' response is considered by letting customers to actively maximize financial benefit from their response.

If at the beginning, customers buy a demand quantity Q at price P_r, and they produce an outcome product which is described as a predetermined function of consumption $h(Q)$. The profit of customers is estimated as follows:

$$W_0 = h(Q) - Q \times P_r \tag{8}$$

When customers participate in the incentive program and reduce the electricity quantity ΔQ, the outcome product, and the electricity cost reduce to $h(Q-\Delta Q)$ and $(Q-\Delta Q)\times P_r$ respectively. At the same time, customers receive an incentive payment from utilities $\Delta Q P_c$. Consequently, the new profit of customers is as follows:

$$W_1 = \left[h(Q-\Delta Q) - (Q-\Delta Q)\times P\right]_r + \Delta Q P_c \tag{9}$$

Customers aim to maximize their own profit thus the objective function from the customers side is given as follows:

$$\max_{\Delta Q} \left\{\left[h(Q-\Delta Q) - (Q-\Delta Q)\times P\right]_r + \Delta Q P_c\right\} \tag{10}$$

$$\text{subject to} \begin{cases} 0 \le \Delta Q \le Q \\ P_c \ge 0 \\ 0 < h(Q-\Delta Q) \le h(Q) \end{cases} \tag{11}$$

The first constraint means that the reduction is not negative, and it has an upper limit depending on actual consumption of customers. In the second constraint, the incentive price should be greater than or equal to zero so that customers are encouraged to participate. The third constraint implies that the outcome product of customers is not negative and it has an upper limitation.

In this maximization process, it is important to estimate the dependence of outcome product of customers on electricity quantity $h(Q)$. For simplification, the outcome product can be modelled as a logarithmic function, derived based on the clustering approach proposed in [31], of the quantity of electricity as given below:

$$h(\xi) = k \times h_0 \times \log\left(\frac{\beta \times \xi \times \xi_0}{\xi_0}\right) \tag{12}$$

where, k and β are constant. $k \times h_0 = k \times (Q \times P_r)$ is the estimate of original profit. ζ is the electricity demand and ζ_0 is the minimum level of electricity demand. The reason for this function selection is that the outcome product may increase quickly at the beginning, but reach to some limitation at some certain level of electricity consumption. This is explained with further details and result demonstration in Subsection 4.3.

4. Results and Discussions

In this section, a dataset for NSW, Australia is acquired to validate the proposed scheme. The scheme is tested in both scenarios of customers' responses which are linear response and restricted response.

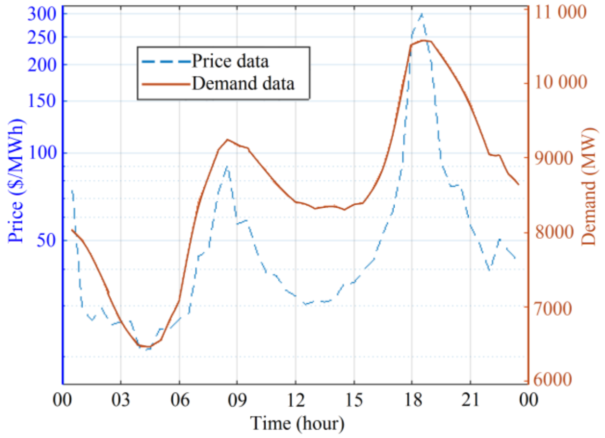

Fig. 6. Profiles of electricity demand and price on 12th of July 2016

Table. 1.
Number of spikes and non-spikes in training dataset

Day	Time	Demand (MW)	Spot price ($/MWh)	Retail price ($/MWh)
12th of Jul 2016	8:30 hrs	10586.72	299.8	221.9

4.1. Data Description

A demand and price dataset for NSW, Australia which is acquired from AEMO [26] is used to validate the proposed model in this study. More specifically, the dataset for 12th of July 2016 is in consideration and the variation of demand and price in this dataset is plotted in Fig. 6.

It can be seen from Fig. 6 that electricity price follows electricity demand closely. It tends to go up when there is a rise in demand, and tends to go down when demand decrease. It is noted from the above figure that price experiences a spike of nearly 300 *$/MWh* at 18:30 *hrs*. This is mainly due to the high value of demand at this time. It is noted that the spot price surpasses the retail price at this moment. The information about demand level, spot price and retail price are given in Table I. In this table, while spot price is acquired from AEMO, the retail price is obtained from the annual report for a typical retail customers of NSW from the Australian energy market commission (AEMC) [32].

It can be seen from Table 1 that the spot price is much higher than the retail price. In this incident, if utilities buy 10586.72 MW with a price of 299.8 ($/MWh) and sell it with a price of 221.9 ($/MWh), they suffer the loss of 10,586.72 MW×(299.8$ – 221.9$)= 824,705.49 $ each hour.

In order to reveal the information of spot price, the bidding data have been acquired from AEMO for this data point. The obtained bidding curve is given in Fig. 7. Also, in this figure, the bidding data is fitted against the price function following (6) and the fitted line is presented as a red continuous line. Furthermore, demand requirement from NSW is plotted as a dashed black line. The meeting point between demand and generation from the bidding curve results in a present spot price.

It can be seen from Fig. 7 that if electricity quantity decreases, the spot price may reduce significantly. Now, it is assumed that the utilities can trigger the customer incentive program and encourage customers to reduce the demand. The next step is to determine the response from the customers. As discussed in Section 3.3, customers may have different response strategies, and each strategy may have strong impacts on the scheme application. Two typical schemes namely linear response and restricted response, which have been discussed in Section 3.3, are investigated in the following subsections.

4.2. Linear Response of Customers

In this subsection, the response from customers is assumed to be linearly dependent on the incentive payment as described in (7). With this dependence, financial losses for utilities are analyzed and sensitivity of customers' response is investigated.

4.2.1. Analysis of Financial Losses for Utilities

Utilities financial losses, including two components namely trading loss and incentive payment, can be greatly impacted by changes of incentive price following equation (3). These two components together with the total financial loss for utilities are estimated at different levels of incentive price and the results are presented in Fig. 8. It is noted that the response sensitivity of customers (*i.e.* slope k_r in (7)) is assumed to be at a typical value of 0.0015.

Fig. 8 shows linear relationship between incentive price and customers' response. As a result, the incentive payment incurred by utilities sees a quadratic growth (as presented as the green dash-dot line). At the same time, demand quantity reduction leads to the decline of spot price and thus creates drop in trading loss for utilities as shown using the black dashed line in Fig. 8.

The summation of trading loss with incentive payment results in the total financial loss for utilities as presented in the continuous blue line. It is clear that this total financial loss reduces significantly when incentive price increases from \$0/MWh to \$131/MWh; however after this incentive price, the loss reverses and starts to increase. From the variation of the total financial loss for utilities, a minimum value can be determined as presented as the red star point. At this point, incentive price is \$131/MWh (i.e., about half of

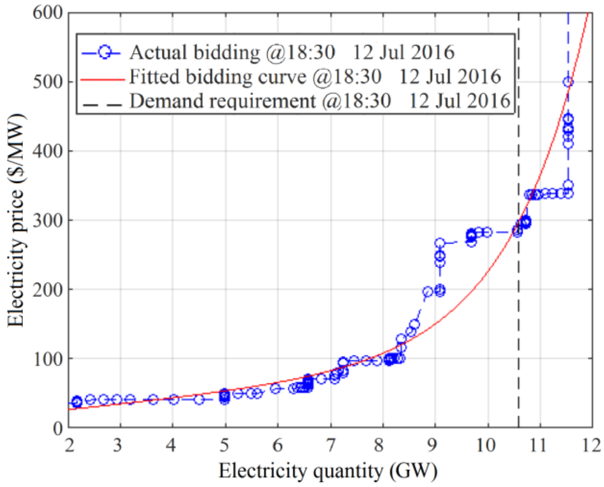

Fig. 7. Dependence of spot price on electricity quantity (demand)

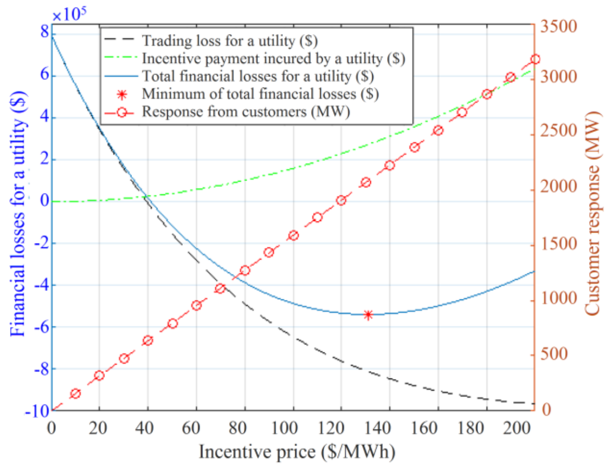

Fig. 8. Utility loss and linear customers' response at different incentive prices

the retail price), and customers reduce 2,080 MW (*i.e.*, about 19.6% of the demand quantity). This reduction leads to the significant drop of utilities' financial loss as presented at the red star point in Fig. 8. It is noted that the total financial loss turns to be negative meaning that utilities can earn profit again with the proposed incentive scheme.

4.2.2. Analysis of Customers' Response Sensitivity

To reveal the dependence of financial loss for utilities on the response sensitivity, sensitivity level (k_r) is varied from 0.001 to 0.005. The results are obtained and presented in Fig. 9.

Fig. 9 shows that at each response sensitivity level, the relationship between financial loss and incentive price changes considerably. Accordingly, the obtained optimum incentive price and minimum financial loss for utilities are altered. With higher sensitivity (*i.e.* higher value of k_r), the optimum incentive price becomes lower. At the same time, the minimum utility loss has reduced noticeably with the higher response sensitivity. The optimization results for different slope k_r are given in Fig. 10.

Fig. 10 shows that when the sensitivity of customer response is stronger (*i.e.*, higher value of slope k_r), both the optimum incentive price and minimum financial loss for a utility becomes smaller.

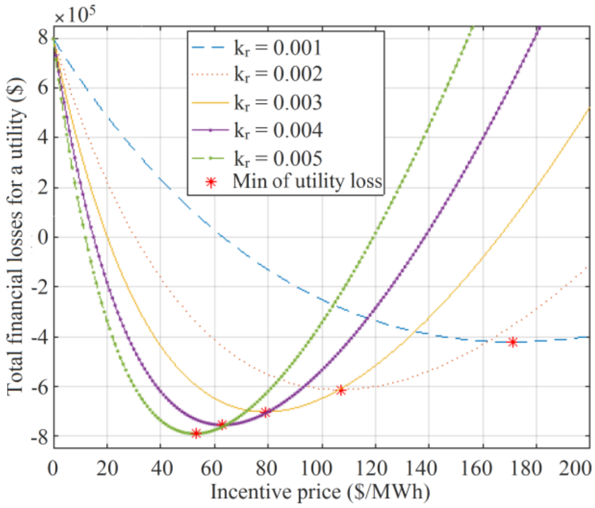

Fig. 9. Impacts of customers' response sensitivity to total financial loss for utilities

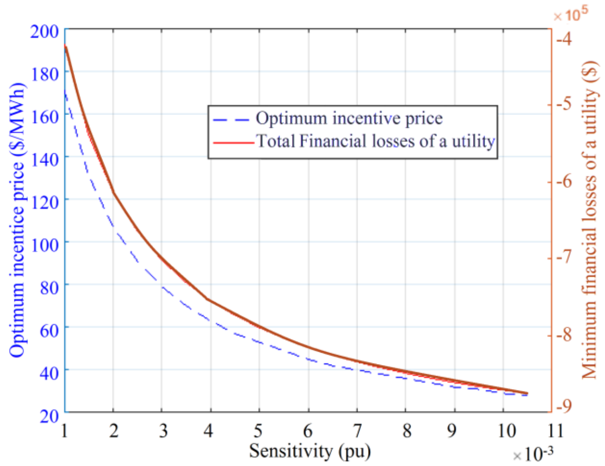

Fig. 10. Optimum incentive price and total financial loss for utilities at different sensitivity levels

4.3. Restricted Response from Customers

Although linear response from customers is handy, it may be too naïve for actual application. In this subsection, the customers' response is assumed to be restricted with a given outcome product loss scenario which has been discussed in Subsection 4.3.2.

4.3.1. Outcome Product Losses for Customers

The outcome product losses for customers are described in (12). In this equation, it is assumed that the customers may have less profit if customer demand reduces. The parameters of equation (12) can be determined based on the customer information. Typically, it can be assumed that coefficients k and β are 1 and 100, respectively. The outcome product together with electricity bill and customer profit change along with the variation of electricity quantity consumption as presented in Fig. 11.

It can be seen from Fig. 11 that while the electricity bill increases linearly, the outcome product experience logarithmic growth along with the electricity quantity. The profit of customer is determined by subtracting the outcome product to the electricity bill; consequently, the profit of customers increases strongly at the beginning, but does not increase much when electricity quantity increases (as shown in the red dash-dot line). This profit representation limits the level of energy use of customers in normal condition because the customers cannot gain more profit even if they try to buy more electricity.

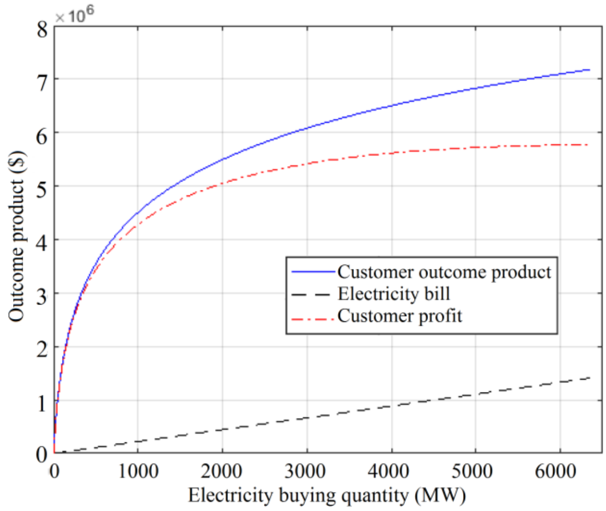

Fig. 11. Outcome product, electricity bill and profit for customers at different levels of electricity quantity

4.3.2. Cost Effective Analysis

The response of customers is strongly dependent on incentive price offered by utilities. With three typical incentive prices of \$40/MWh, \$60/MWh and \$80/MWh, the customers' profits are determined using (9) and the results are plotted against electricity quantity reduction in Fig. 12. Also in this figure, the maximum customer profits are indicated as black star points for different incentive prices

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Fig. 12 shows, at a given incentive price offered by utilities, the profit of customers varies with electricity quantity reduction. From this variation, an optimum point can be determined by maximizing customer profit. For example, at an incentive price of \$60/MW, customers tend to response by reducing 1152MW (10.9%) and accordingly achieve a maximum profit.

At the same time, the change of incentive price will lead to variation of total financial loss for utilities. The changes of total financial loss for utilities and profit for customer are obtained and represented in Fig. 13.

It can be seen from Fig. 13 that both financial loss for utilities and profit for customers experience great variation when changing the incentive price. When the incentive price is less than a certain value (i.e., Pc =

$10/MWh), customers may not interest in response to the scheme, thus both the financial loss for utilities and profit for customers are constant. After this price (i.e., when Pc is greater than $10/MWh), the profit for customers increases dramatically. At the same time, financial loss for utilities experience drastic drop when incentive price increase from $10/MWh to $117/MWh. When incentive price continues to increase above $117/MWh, while customers' profit keeps rising dramatically, utilities' losses change direction and increase slightly. Since the incentive price is offered by utilities, they may consider operating the scheme at a price of $117/MWh, which result in minimum loss of utilities. It is noted that this minimum loss is negative indicating that utilities earn profit again when applying the proposed scheme.

This analysis may be significantly meaningful to the utilities since it can evaluate the possible response of customer and announce an appropriate incentive price for the customer incentive scheme.

5. Conclusion

In this paper, a customer incentive scheme is proposed for building an effective DR program. In this program, an incentive scheme is proposed for utilities with an incentive price to encourage customers to reduce their electricity demand to a certain level. An optimization problem is formulated to minimize the utility loss based on changing the offered incentive price. Linear approach is employed to solve the problem and the optimum incentive price is determined at the point where utility loss is at a minimum level.

Furthermore, it is revealed that customers' responses do have strong impacts on the optimization process of the proposed scheme. Consequently, two typical customers' response scenarios which are linear response and restricted response are investigated. It has been found that with higher sensitivity level, the optimum incentive price is lower, and the utility loss becomes lower as well.

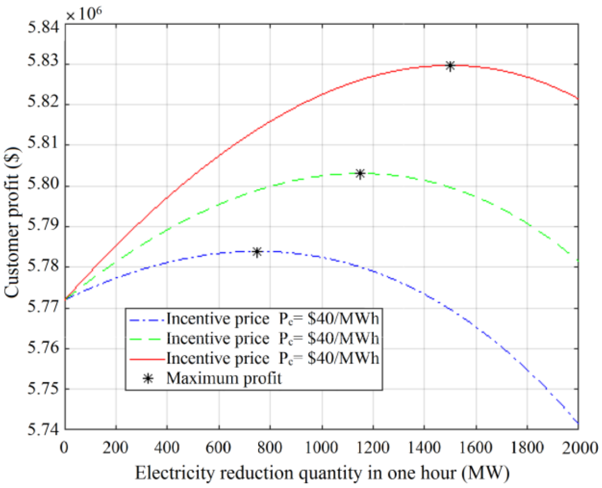

Fig. 12. Changes of customer profit against electricity quantity reduction for typical incentive prices of $40/MWh, $60/MWh and $80/MWh

A small dataset for NSW, Australia is employed as a case study to investigate the effectiveness of the proposed incentive scheme. The obtained results show that the proposed scheme can successfully help utilities to minimize their financial losses and assist customers to maximize their profit.

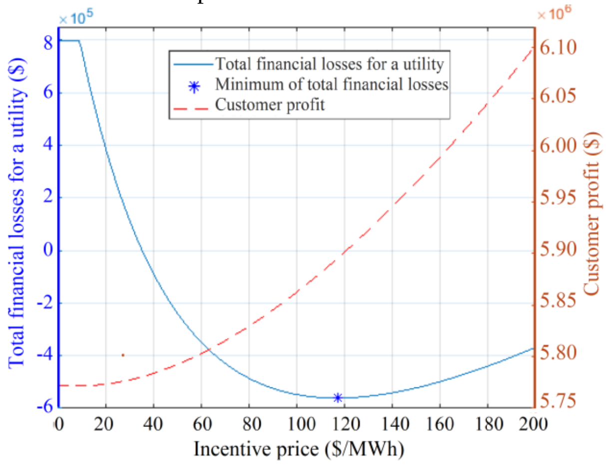

Fig. 13. Total financial losses for a utility and customer profits at different incentive prices

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