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A Scoring Rule-based Truthful Demand Response Mechanism

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Abstract

Demand Response (DR) has been extensively studied as one of the important features of smart grid. The DR strategies can be grouped into two categories, one is incentive-based DR and the other is pricing-based DR. Our work focuses on DR involving both pricing factor and incentive factor using scoring rule. In the literature, several DR mechanisms have been proposed, however, most studies have not focused on the cooperation among consumers although it is important to devise an efficient and stable DR. In this paper, we propose a cooperative demand response mechanism by using a truthful allocation mechanism with scoring rule. The brief ideas of our model are the following: the consumers will be rewarded a discount on the price to measure up how well they predict demand shift. A reward mechanism is based on a strictly proper scoring rule. This mechanism is applied between consumer agents (CA) to Cooperative Demand Response System (CDRS) and Generation Company (GENCO). The proposed mechanism is tested on real data provided by Chubu Electric Power Company and we show that this mechanism is capable of reducing peak demand.

Keywords: Mechanim Design, Scoring Rule, Demand Response

1. Introduction

With the growing needs of environmental sustainability and continuous change in electric power deregulation, smart grid becomes an inevitable choice for the society. As one of the important features of smart grid is Demand Response (DR). DR is gaining importance in designing grid functionalities specially at the end user (consumers) level. Formally speaking, DR is a mechanism that influences the consumers to modify their energy usages from the normal consumption patterns in response to the changes in the price of electricity over time [2].

In order to fully utilize the DR capability, smart houses had already start to adopt devices which can be controlled, maintained, monitored and even scheduled as necessary. Smart house technologies make all electronic devices around the house to act ”smart” and become more autonomous. Most of the important appliances in the future will take advantage of this technology through home networks and the Internet. Such feature of smart grid is a way for ordinary electronics and appliances to communicate among themselves, consumers and even higher entities such as GENCOs. In such an environment, consumers (actually a consumer agent, refereed as CA hereafter, will be responsible to take such decision in conjunction with smart-meter) can respond to day-ahead dynamic pricing signal effectively and also intelligently managing and scheduling devices thereby flattening out peak demand and achieving better resource utilization.

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DR has been studied in various fields. DR strategies can be grouped into two general categories, one is pricing-based DR and another is incentive based DR. In the pricing-based DR [21,26], consumers dynamically adjust their consumption according to the time varying pricing while maximizing their payoffs. And for incentive based DR [8,6], consumers are given incentives in payment, to reduce their consumption in response to the system reliability. Pricing-based DR such as RTP (Real-Time Pricing) has problem in terms of an efficient stable power system operation, because it is too difficult to know in advance how much consumers actually participate in DR. As an example, [1] shows that RTP mechanisms do not necessarily lead to peak-to-average ratio reduction, because large portions of load may be shifted from a typical peak hour to a typical non-peak hour. When attention is paid only to efficiency and stability, "direct load control" in which a power company controls the amount of electricity consumption of consumers from outside is most effective, but it has problem in terms of usability. In addition, most studies have not focused on the cooperation among consumers, but it is important to develop efficient and stable DR.

On a different note, in order to numerically measure the actual realization of a probabilistic event which will forecast ahead, scoring rule was defined [15,4]. Moreover, it binds the assessor to make a careful prediction and hence truthfully elicit his/her private preferences. That is why, scoring rule has been applied successfully while designing a truthful incentive mechanism in a diverse applications such as voting rules [31] [19]. Strictly proper scoring rules can be employed by a mechanism designer to ascertain that agents accurately declare their privately calculated distributions, reflecting their confidence in their own forecast. The applicability of scoring rule is being investigated in field of smart-grid. For instance, [24] presented a methodology for predicting aggregated demand in smart grid.

However, it is not enough to apply scoring rule to our model because our model uses auction for task allocation. When using scoring rule alone, agents are in fact able to *misreport* their belief in order to get task. Therefore, we also apply Viclrey-Clarke-Groves Mechanism [30,9,16] to our model. The applicability of VCG mechanism is being investigated in field of demand side management. For instance, [25] presented a VCG mechanism for demand side management programs to encourage efficient energy consumption among the users. In our model, we combine scoring rule and VCG mechanism to truthfully elicit agent's private preferences.

This paper presents a scoring rule based truthful cooperative demand response mechanism for CAs provided by the GENCO in response to the dynamic day-ahead time dependent pricing. The proposed method can be viewed as a bridge between incentive based DR and pricing based DR. The main ideas of our model can be summarized as follows: the consumers will be rewarded a discount on the price to measure how well they predict the shift demand that represents shifting the devices/loads towards specified time periods. The reward mechanism is based on a strictly proper scoring rule and VCG mechanism. The scoring rule is chosen to work with continuous variable (the normal distribution, as in the proposed method) and measure how accurate the prediction could be. The Continuous Ranked Probability Score [15] possess such characteristics. In our mechanism, CA has incentive to participate in CDR using *The Wisdom of Crowds* [27] such as lot of CAs prediction is better than a CA prediction. In addition, our mechanism has several desirable properties such as *truthfulness* and *individual rationality* and *scalability*.

The contributions of this paper are summarized as follows:

- We propose a scoring rule based truthful cooperative demand response mechanism for GENCO to encourage efficient peak cut. The proposed model can be viewed as a bridge between incentive based DR and pricing based DR. The consumers will be rewarded a discount on the price to measure up how well they predict the shift demand.
- We investigate some of the desired properties of our model. Such as, *truthfulness* and *individual-rationality* of the proposed mechanism are proved and we fulfill those properties by combining scoring rule and VCG mechanism.
- We show that, each consumer has incentive to

cooperate with each other by comparing CDRS and Singleton in experimental results. In addition, proposed model has *scalability* that the even-though number of CA increases, *Wisdom of Crowd* [27] can work and the accuracy of prediction of CDRS also increase. We show that the larger the number of CA, gives better accuracy of prediction in the experiment.

- We tested proposed mechanism on real data provided by Chubu Electric Power Company and we validated that, this mechanism is capable to reduce peak demand.

The remainder of the paper is organized as follows, Firstly, we describe our model of cooperative demand response. Second, we describe the details of CDR Algorithms and a mechanism. Third, we describe the results of the experiments and our evaluation. Fourth, we describe the relative works. Finally, we conclude with a discussion of possible avenues for future work.

2. Cooperative Demand Response Model

We begin the situation where N consumer agents (CAs) use a same generation company (GENCO). In this paper, we represent cooperation among CAs introducing CDRS (Cooperative Demand Response System) that represents a set of CAs. Each CA has a smart meter that communicates with the various devices at the CA and also GENCO. Each CA has two types of devices, one is "base load" that can not be shifted, such as lights or computers. Another is "flexible load" that can be shifted, such as AI robots or household electrical appliances. GENCO will try to flatten out the peak demand by incentivizing CA to cooperative shift flexible load consumption. CA will try to maximize the reward from GENCO. The reward depends on actual shift demand and accuracy of prediction.

Our model assumes a dynamic "day-ahead" pricing signal [17], CAs receive their prices one day in advance. This pricing signal offers users more certainty than other common implementations of dynamic pricing [21,18], such as "hour-ahead" or real-time pricing. With day-ahead pricing, CAs can schedule their device usage for the upcoming day so as to optimize their amount spent and willingness to shift their device usage. Hour-ahead or real-time pricing would force the ECC (Energy Consumption Controller) to use less optimal scheduling algorithm to solve an online knapsack problem. We note, however, that our algorithm can be easily adapted to hour-ahead pricing.

As a mechanism is design to incentivize CAs for providing private probabilistic information accurately (truthfully) and to the best of their forecasting ability, scoring rule is being applied in this model. Especially, strictly proper scoring rules can be employed by a mechanism designer to ascertain that agents accurately declare their privately calculated distributions, reflecting their confidence in their own forecast. The detailed flow of information and task assignment process are presented in Figure 1. As we can see, GENCO will send the price information as a signal to CAs. The price signal is typically determined based on the generation costs of electricity.

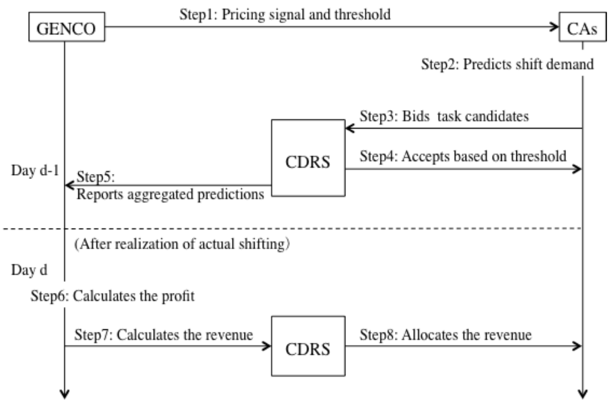

Fig. 1. CDR model flow

CA located in consumer's household integrated with ECC. Therefore, it can access the local information and data of that particular consumer. This information includes device usage schedule, duration, energy consumption, etc. CA also keeps track of the previous schedule prediction. Using such information plus the day-ahead dynamic pricing, CA makes a pre-schedule plan of different devices based on its forecasting accuracy and consumer's preferences. However, it will report CDRS the prediction confidence in a form of Gaussian distribution and tentative schedule of assigned devices. For each device, CA calculates its uncertainty over the error it expects to make using a statical model of random errors. So, CA makes its prediction through a Gaussian Distribution. This assumption is based on the sampling of higher number of devices, since eventually an CDRS must handle a wide range of devices. *Central Limit Theorem* tells us in a case of wide range of events, the probability distribution that describes the sum of random variables tends towards a Gaussian Distribution as the sum approaches towards infinity. According to that, we can say that, in the perspective of CDRS, reporting error in the form of Gaussian Distribution is valid and portrays some form of accuracy.

We assume that each CA is various environment such as communication speed and load composition. Therefore, our model achieves the cooperation by combining scoring rule and VCG. Our model has some of the desired properties such as *truthfulness* and *individual rationality* and *scalability* based on *The Wisdom of Crowds* such as a lot of CAs prediction is better than a CA prediction.

3. Algorithm

In this section, we introduce detail of the CDR algorithm. First of all, set of CAs can be represented as $N = \{1, 2, ...n\}$ and CAs try to maximise the expectation utility. Each CA has type $\theta_i \in \Theta_i$ which determines the preferences over different outcomes; i.e $v_i(a, \theta_i)$ is the value of CA i with type θ_i for outcome $a \in A$. In our model, we use VCG mechanism and the choice rule $g : \Theta \to A$ and payment rule $p : \Theta \to \mathbb{R}$ and utility function are presented in Eq.(1) and Eq.(2) and Eq.(3).

$$g(\theta) = \arg\max_{a \in A} \sum_i v_i(a, \theta_i) \tag{1}$$

$$p_i(\theta) = \sum_{j \neq i} v_j(g(\theta_{-i}), \theta_j) - \sum_{j \neq i} v_j(g(\theta), \theta_j) \tag{2}$$

$$u_i(\theta_i) = v_i(a, \theta_i) - p_i(\theta) \tag{3}$$

Step1: Pricing signal and threshold

GENCO estimates the total demand curve in the next day and assumes threshold Th that signifies the goal of peak cut. In general, time periods that has larger demand is assigned high price, In order to shift and control demand [3]. In our model, we assume that there exist exactly two different price levels $price_h > price_l$. Time interval t of each is expressed in Eq.(4).

$$price^t = \begin{cases} price_h, & if \quad TotalDemand^t \geqslant Th \\ price_l, & if \quad TotalDemand^t < Th \end{cases} \tag{4}$$

The intervals during which $price^t = price^h$ are considered to be peak-intervals, at which consumption needs to be reduced.

Step2: Predicts shift demand

CAs predict the shift demand $sd^p_{i,t}$ based on price signal and load composition. CAs have two type of devices, one is ”base load” and another is ”flexible load”. CAs predict the demand of flexible load in t_h. Therefore, predicted shift demand of CA i in specific time periods t is presented in Eq.(5). where DV_i is a set of flexible load of CA_i.

$$sd^p_{i,t} = \sum_{j \in DV_i} ShiftDevicesDemand^p_{j,t} \tag{5}$$

In case CAs do not behave as predicted, it may lead to retard in planned production of GENCO and decrease the peak-to-average ratio. In this model, we introduce a scoring rule to incentivize CAs for providing private probabilistic information truthfully. GENCO calculates the reward for CAs based on prediction of task achievement and prediction of confidence. Our model is dealing with devising a scoring rule for multi-item prediction. Therefore, conventional scoring rule with single item, such as *Brier score* [5] is of no use for this mode. In order to rightfully incentivize the CA to make their prediction of device shifting for multiple items rightfully; the continuous ranked probability score (CRPS) is applied [15]. CRPS is a strictly proper scoring rule that is used for continuous variables since the traditional forms of proper and strictly proper scoring rules usually do not work with continuous variables. In the proposed method, *Gaussian Distribution* is used to model the consumer's device shifting prediction and associated confidence. The usage of CRPS is investigated before in distributed power system operation to rightfully score the distributed energy resources [23]. CRPS is able to measure the closeness of the prediction that means how close a prediction to realized event where higher value is assigned to close prediction. The relative prediction error $e_{i,t}$ of CA_i in each time periods as presented in Eq.(6).

$$e_{i,t} = \frac{sd^a_{i,t} - sd^p_{i,t}}{sd^p_{i,t}} \tag{6}$$

where $sd^a_{i,t}$ shows the actual shift demand. Lets assume each CA i reports its relative prediction error in a form of uncertainty over it, represented by *Gaussian Distribution Function* $N(\mu = 0, \sigma^2_{i,t})$. Let $\sigma_{i,t}$ be CA_i confidence of prediction, CRPS is presented in Eq.(7).

$$\begin{aligned} &CRPS(N(\mu = 0, \sigma^2_{i,t}), e_{i,t}) \\ &= \sigma_{i,t}\left[\frac{1}{\pi} - 2\varphi\left(\frac{e_{i,t}}{\sigma_{i,t}}\right) - \frac{e_{i,t}}{\sigma_{i,t}}\left(2\Phi\left(\frac{e_{i,t}}{\sigma_{i,t}}\right) - 1\right)\right] \end{aligned} \tag{7}$$

where the probability density function and cumulative distribution function for *Gaussian Distribution Function* are denoted as φ and Φ, respectively. The notation $CRPS(N(\mu = 0, \sigma^2_{i,t}), e_{i,t})$ can be simplified using $CRPS_{i,t}(\theta_i)$.

Figure 2 shows realization of scoring factors for different errors and confidence level. From the graph presented in Figure 2, it is import to notice that,

- when a CA is highly confident about its prediction (*e.g* $\sigma_{i,t} = 0$);then highest score is rewarded i.e when the realized absolute error is zero.
- when the realized error is relatively higher, then CA will be benefitted to report lower confidence (*e.g higher values of* $\sigma_{i,t}$).

Therefore, CAs can maximize the score to report the uncertainty of prediction accurately.

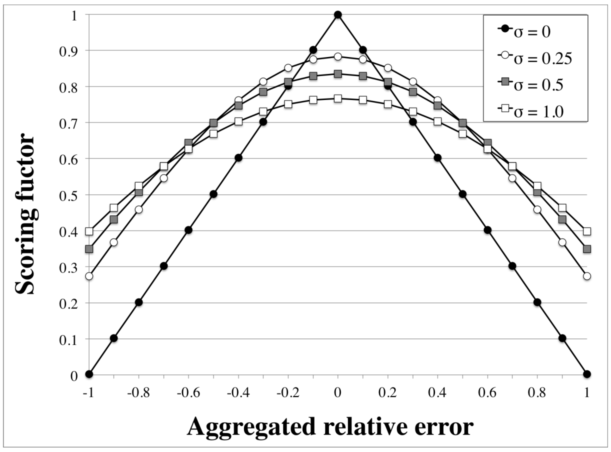

Fig. 2. A CRPS scoring mechanism for different errors

Step3: Bids task candidates

CAs bid for the task candidates to CDRS. In this model, a single task means that CA shifts a "flexible load" from specific t_h to specific t_l. A bid consists of four elements as presented in Table 1. In this paper, each CA selects t_h and t_l randomly. Each CA can bid a defined number in advance.

A bid consists of three elements, beginning of shift demand t_h, end of shift demand t_l, shift demand capacity $sd^c_{i,t}$. In this paper, each CA selects t_h and t_l randomly. Each CA can bid a defined number in advance.

Step4: Accepts based on threshold

CDRS accepts bids from CAs based on threshold. First, CDRS sorts all bids based on $sd^p_{i,t} * (1 - \sigma_{i,t})$. That is, larger the contribution of peak cut, higher is the accept rate. Next, CDRS accepts bids based on following constraints in Eq.(8) and Eq.(9).

[Conditions of Acceptance]

$$TotalDemand_{t_h} - \sum_{b \in Bids_t} sd^p_{b,t} \geqslant Th \tag{8}$$

$$TotalDemand_{t_l} + \sum_{b \in Bids_t} sd^p_{b,t} < Th \tag{9}$$

where $Bids_t$ means sorted all bids. Eq.(8) shows that total demand in t_h is always larger than threshold. That is, this model can not conduct peak cut more than necessary in order to guarantee the safety. Eq.(9) shows that total demand in t_l is always smaller than threshold. That is, this model can not create new peak demand.

Step5: Reports aggregated prediction

CDRS aggregates the prediction from CAs and reports it to GENCO. The task of achieving the prediction and actuality can be expressed as $sd^p_{c,t} = \sum_{i\in N} sd^p_{i,t}$, $sd^a_{c,t} = \sum_{i\in N} sd^a_{i,t}$, respectively. The relative error and confidence level of CDRS can be expressed as, $e_{c,t} = \frac{sd^a_{c,t} - sd^p_{c,t}}{sd^p_{c,t}}$, $\sigma^2_{c,t} = \frac{\sum_{i\in N}(sd^p_{i,t} * \sigma_{i,t})^2}{\left(\sum_{i\in N} sd^p_{i,t}\right)^2}$, respectively. Therefore, the as the number of CA increases, the relative error of CDRS decreases. In the experiment, we show that, as the number of CA increases, prediction accuracy increases.

Step6: Calculates the profit

GENCO calculates the profit based on production cost and actual shift demand of CAs. The GENCOs usually operate multiple plants of different types, *e.g.* gas, hydroelectric (hydro), renewables and coal. These plants may be categorized as base, intermediate, and peak-load. The base-load plants generally have a higher capital cost but low operating cost, and thus run all of the time (*e.g.*, hydro, nuclear). Intermediate load plants (*e.g.*, coal) have a higher operating cost, and peak load plants (*e.g.*, gas turbines) have the highest operating cost. In any given time periods, if CDRS demand exceeds the base-load capacity, the generator turns to the intermediate-load plants and then finally, to peak-load plants to generate additional electricity. Lets c_h and c_l represent the peak-load production cost in t_h and intermediate production cost in t_l respectively and the difference $c_h - c_l$ represents the $costValue_t$, the profit of GENCO is presented in Eq.(10).

$$profit^G_t = costValue_t \times sd^a_{c,t} \tag{10}$$

In this paper, the production cost is based on real data [11,29].

Step7: Calculates the revenue

GENCO calculates the payment based on prediction and confidence of CDRS's task achievement. Let the price difference $p_h - p_l$ represents the sv_t, the payment is presented in Eq.(11).

$$v_{c,t}(a,\theta) = CRPS_{c,t}(\theta) \times sv_t \times sd^a_{c,t} + \lambda \times profit^G_t \tag{11}$$

The payment is composed of four factors. The *CRPS* (scaled between 0 and 1) is the "accuracy factor" that incentivizes CDRS to provide as accurate description as possible for its relative prediction error. The sv_t is the "shift factor" that constitutes the actual price paid by the GENCO to CDRS. The $sd^a_{c,t}$ is the actual shift demand of CDRS in settlement time period t, which is independently observed by the GENCO. The $\lambda \times profit$ $(0 < \lambda \leqslant 1)$ is the fraction of production profit. Since GENCO needs to make profits by CDR, GENCO allocates a fraction of production profit. The significant point of Eq.(11) is that it considers not only the different price, but also incentive to provide accurate description. Therefore, our model can remove the "unethical" ways such as falsehood and guarantee the safety.

Step8: Allocates the revenue

CDRS allocates the payment to CAs based on contribution rate in the total reward and part of GENCO's profit. The contribution rate is composition of actual shift demand and prediction of accuracy. The reward of CA_i is presented in Eq.(12).

$$v_{i,t}(a,\theta_i) = \frac{CRPS_{i,t}(\theta_i) \times sd^a_{i,t}}{\sum_{j\in N} CRPS_{j,t}(\theta_j) \times sd^a_{j,t}} \times v_{c,t}(a,\theta) \tag{12}$$

where $v_{c,t}(a,\theta)$ shows the Eq.(11).

Algorithm properties

Proposed algorithms have several desirable properties.

Truthfulness

Truthfulness is an important measure to validate an agent based protocol or strategy. One obvious way to deal with truthfulness is to set a mediator which will observe the behavior of all participated agents and thus ensures all agents report truthfully. However, mediator based protocols impose several difficulties such as centralization, private information elicitation, etc. At the same time, as the number of agent increases, Then it will become difficult for a single mediator to control the information. Therefore, the best way to ensure is to design the protocol such a way that, its always the best for an agent to report truthfully in order to get maximum expected utility. Our model is *strategy-proof* by using VCG mechanism and Scoring rule.

Theorem 1. *CDR is strategy-proof for CAs with quasi-linear preferences.*

Proof. We prove that CDR is strategy-proof, such that truth-revelation is a dominant strategy for each CA, from which allocative efficiency follows immediately because the choice rule $g(\theta)$ computes the efficient allocation in Eq.(1).

The utility to CA i from strategy $\widehat{\theta_i}$ is:

$$
\begin{aligned}
&u_i(\widehat{\theta_i})\\
&= v_i(g(\widehat{\theta}),\theta_i) - p_i(\widehat{\theta})\\
&= v_i(g(\widehat{\theta}),\theta_i) + \sum_{j\neq i} v_j(g(\widehat{\theta}),\widehat{\theta_j}) - \sum_{j\neq i} v_j(g(\widehat{\theta_{-i}}),\widehat{\theta_j})
\end{aligned}
$$

Ignoring the final term, because $\sum_{j\neq i} v_j(g(\theta_{-i}),\theta_j)$ is independent of an CA i's reported type.

we prove that truth-revelation $\widehat{\theta_i} = \theta_i$ solves:

$$
\begin{aligned}
&\max_{\widehat{\theta_i}\in\Theta_i}\left[v_i(g(\widehat{\theta_i},\widehat{\theta_{-i}}),\theta_i) + \sum_{j\neq i} v_j(g(\widehat{\theta_i},\widehat{\theta_{-i}}),\theta_j)\right]\\
&= \max_{\widehat{\theta_i}\in\Theta_i}\left[v_i(x,\theta_i) + \sum_{j\neq i} v_j(x,\widehat{\theta_j})\right] \qquad (13)
\end{aligned}
$$

where $x = g(\widehat{\theta_i},\widehat{\theta_{-i}})$ is the outcome selected by the mechanism. The only effect of the CA's announced type $\widehat{\theta_i}$ is on x, and the CA can maximize Eq.(13) by announcing $\widehat{\theta_i} = \theta_i$ because v_i is strictly proper scoring rule in Eq.(11) and Eq.(12). As shown Eq.(11), the CRPS part of function is a strictly proper scoring rule and the entire function in Eq.(11) is an affine transformation of this rule (since it only involves multiplication and addition with other factors which do not depend on the reports made by the agent). Hence, Eq.(11) and Eq.(12) are also strictly proper [15]. Then the mechanism computes $g(\widehat{\theta_i},\widehat{\theta_{-i}})$ to explicitly solve:

$$
\begin{aligned}
&\max_{a\in A} v_i(a,\theta_i) + \sum_{j\neq i} v_j(a,\widehat{\theta_j})\\
&= \max_{a\in A} \frac{CRPS_{i,t}(\theta_i)\times sd^a_{i,t}}{\sum_{j\in N} CRPS_{j,t}(\theta_j)\times sd^a_{j,t}} \times v_{c,t} + \sum_{j\neq i} v_j(a,\widehat{\theta_j})
\end{aligned}
$$

Truth-revelation is the *dominant strategy* of CA i, whatever the reported types $\widehat{\theta_{-i}}$ of the other CAs. □

Individual rationality

Individual rationality is ascertained for all CAs in CDRS, as they all have non-negative expected gain from participation. Our model is *individual-rationality* by using VCG mechanism.

Theorem 2. *CDR is individual-rational with quasi-linear preferences.*

Proof. To show individual-rationality, we show that the utility to CA i in the equilibrium outcome of the mechanism is always non-negative. We can assume truth-revelation in equilibrium. The utility to CA i with type θ_i is:

$$
\begin{aligned}
&u_i(\theta_i,\theta_{-i})\\
&= v_i(g(\theta),\theta_i) - \left(\sum_{j\neq i} v_j(g(\theta_{-i}),\theta_j) - \sum_{j\neq i} v_j(g(\theta),\theta_j)\right)\\
&= \sum_i v_i(g(\theta),\theta_i) - \sum_{j\neq i} v_j(g(\theta_{-i}),\theta_j) \qquad (14)
\end{aligned}
$$

Eq.(14) is actually the same as VCG mechanism. Hence, the equilibrium outcome of the mechanism is always non-negative. □

Eq.(14) is non-negative because the value of the best solution without CA i, $\sum_{j\neq i} v_j(g(\theta_{-i}),\theta_j)$, cannot be greater than the value of the best solution with CA i, $\sum_i v_i(g(\theta),\theta_i)$. This follows because any choice with agents $j \neq i$ is also feasible with all CAs (monotonicity), and has just as much total value (*no negative externalities*).

Scalability

Scalability is important property in the field of smart grid because there would be so many participants. In our model, the reward is based on actual demand shift and accuracy of prediction using CRPS. We assume that each CA is various environments such as communication speed and load composition. Therefore, the more number of CA increase, *Wisdom of Crowds* [27] can work and the accuracy of prediction of CDRS increase. We show that the large number of CA are better accuracy of prediction in experiment.

4. Experimental Results

4.1. Setting

In this section, some data analysis and simulation results are presented in order to verify the feasibility of the scoring rule based cooperative demand response mechanism. The real parameters are taken based on *Chubu Electric Power Co.,Inc.*, such as the demand curve [10,28] and production cost [11,29]. We conducted 62 days in summer. In each day, we applied a CDR mechanism. The demand prior to CDR is based on above data and perturbed up to 10% by a uniformly distributed random number.

We compared our model with the singleton algorithm in Figure 3. CAs report prediction to GENCO without CDRS and calculate the reward based on Eq.(11). The parameters for our experiments are defined as Table 2.

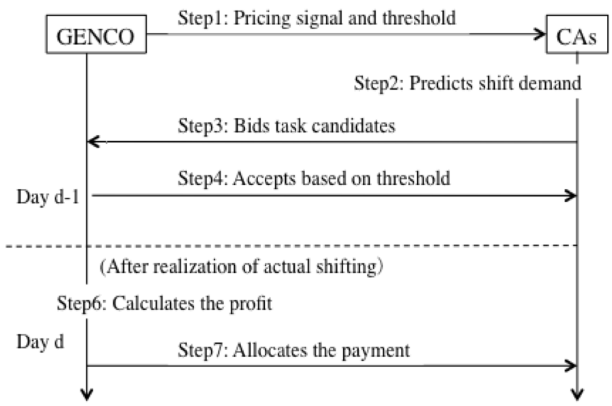

Fig. 3. Singleton model flow

4.2. Results

While the quantitative results of these simulations will vary from market to market, the qualitative results suggest that CDR mechanism can indeed help GENCO and CAs.

Effectiveness of peak cut

Let us first consider the effectiveness in terms of peak cut during half of simulation days. In Figure 4, the vertical axis represents the total energy consumption and the horizontal axis represents the half of simulation hour. We can see that before-demand-curve has the cyclic electricity consumption pattern based on real data and the peak demands of after-demand-curve are always reduced. Therefore, scoring rule and VCG based proposed mechanism is capable to reduce peak demand.

Figure 5 shows the total demand curve and threshold. In Figure 5, $t_{10},t_{11},t_{12},t_{14},t_{15},t_{16},t_{17},t_{20}$ belong to t_h, other belong to t_l. Before-peak-demand is 1292.4 kwh, threshold is 1163.1 kwh, after peak demand is 1218.9 kwh. We can see that proposed mechanism can flatten peak demand without creating a new peak.

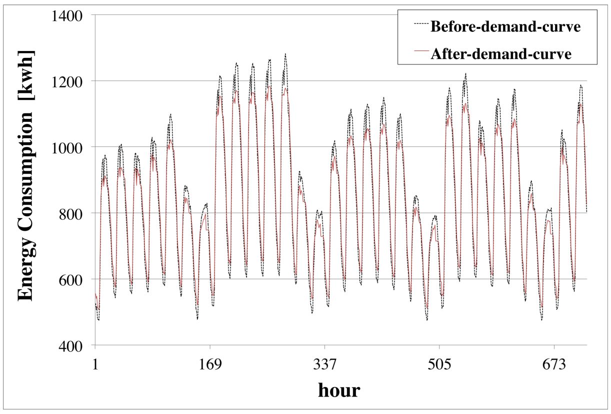

Fig. 4. Energy usage before (black dotted line) and after (red solid line) using of CDR algorithm: 31 days

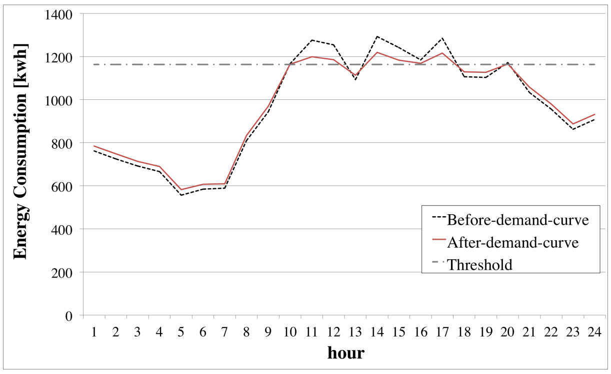

Fig. 5. Energy usage before (black dotted line) and after (red solid line) using of CDR algorithm: 24 hours

CA's average utility: CDRS vs Singleton

Figure 6 shows the CA's average utility (total reward divide by number of CA). In Figure 6, the vertical axis represents the CA's average utility in a day and the horizontal axis represents the total simulation days. We can see that CDRS is always better reward than Singleton. That is, each CA has incentive to cooperate with each other because each CA can increase the utility.

We can see that the utility of CDRS and Singleton are always non-negative. This is because we apply VCG mechanism to our mechanism and *individual-rationality* is ascertained for all CAs.

Scalability: the large number of CA

Table 3 shows scalability of our mechanism considering number of CA and CA's average reward during total simulation days. AVE in the table represents the CA's average utility. We can see that the more number of CA increases, the more increases average utility both CDRS and Singleton. However, the member of CDRS is better than Singleton because the more number of CA increase, the better of prediction accuracy and also utility.

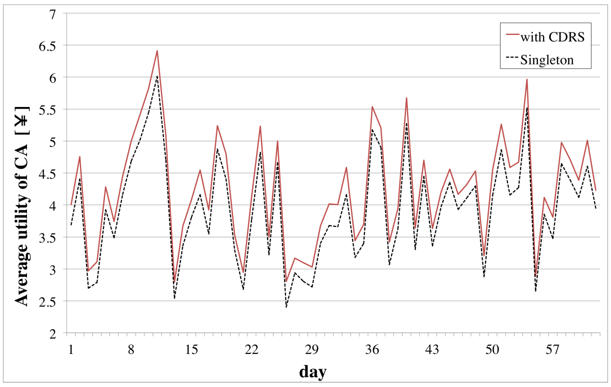

Fig. 6. CA's average utility with CDRS vs Singleton

5. Related Work

In the field of DR, there have been several works that focused on scoring rule [24,7]. [24] presented a methodology for predicting aggregated demand in smartgrid. But these method do not considers demand shift at the device level and do not examine these method by real data simulation. Our model can take heterogeneity at the device level into account and the proposed mechanism is tested on real data.

[7] presented a pricing scheme for smart house environment which takes advantage of both time and incentive based DR using CRPS. But this scheme do not considers the conditions of the demand shift and do not considers the payment to mechanism. Our model can consider the conditions of the demand shift and we combine scoring rule and VCG mechanism to truthfully elicit agent's private preferences.

In addition, most studies [13,12,20,7] have not focused on cooperation among consumers although it is important to devise an efficient and stable DR.

Our model focused on cooperation among consumer agents using CRPS.

There have been a few studies that focused on cooperation among agents. [14] presented a formulation for scheduling demand response among residences when the cost of electricity is known in advance. They deal with cooperation as a utility optimization problem. But they do not consider prediction of demand and scalability of method. [22] focused on demand side management in terms of Virtual Power Plant and they deal with cooperation using market mechanism. But they do not consider demand shift at the device level.

On the other hand, our model achieves the cooperation using scoring rule and develop some of the desired properties such as *truthfulness* and *individual rationality* and *scalability* by applying CRPS and VCG mechanism to our model. In addition, our model can consider demand shift at the device level using bid.

6. Conclusion

DR program is gaining importance in a smart grid environment. Due to the lack of energy supply in comparison with demand, efficient energy management and a DR mechanism is essential. This paper introduces a scoring rule based truthful demand response mechanism considering both pricing factor and incentive factor.

In our model, some of the desired properties such as *truthfulness* and *individual-rationality* are proved. We fulfill those properties by combining scoring rule and VCG mechanism. In addition, our model is that each CA has incentive to participate in CDR using *Wisdom of Crowds* such as a lot of CAs prediction is better than a CA prediction. This model consists of generators, cooperative demand response system and consumers. The scoring system (facilitating *Continuous Ranked Probability Score*) and VCG mechanism are designed such a way that it will incentivize the consumer agents to predict accurately. In the experimental results, we presented that this mechanism is capable to reduce energy consumption and mechanism is scalable.

We will try to model device sensitiveness towards scheduling and apply such mechanism for higher scaled power system. Moreover, another potential future research direction is to integrate device dependency in formulation to make the DR program responding towards the heterogeneity of devices. Moreover, we will try to optimize the threshold to flatten peak demand.

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