

Multi-level Scoring Rule Application for Smart Pricing Scheme

Shantanu Chakraborty Takayuki Ito

Nagoya Institute of Technology, Nagoya

This paper presents an incentive based smart dynamic pricing scheme for consumers facilitating a hierarchical scoring mechanism. This mechanism is applied between consumer agents (CA) to electricity provider agent (EP) and EP to Generation Company (GENCO). Based on the Continuous Ranked Probability Score (CRPS), a hierarchical scoring system is formed among these entities. As CA receives the dynamic day-ahead pricing signal from EP, it will schedule the household devices to lower priced-period and report the prediction in a form of *Gaussian Distribution* to EP. Similarly, EP, reports the aggregated demand prediction to GENCO. Finally, GENCO computes the base discount after running a cost-optimization problem. GENCO will reward EP with a fraction of discount based on their prediction accuracy. EP will do the same to CA based on how truthful they were reporting their intentions on device scheduling. The method is tested on real data provided by Ontario Power Company.

1. Introduction

With the growing needs of environmental sustainability and continuing changes in electric power deregulation, smart grid becomes an inevitable choice for the society. While such grid infrastructure in mind, houses started to adopt devices which can be controlled, maintained, monitored and even scheduled as necessity calls. Smart house technology used to make all electronic devices around a house act “smart” or more autonomous. Recently, smart pricing has attracted much attention as one of the most important demand-side management (DSM) strategies to encourage users to consume electricity more wisely and efficiently [1].

On different note, in order to numerically measure up the actual realization of a probabilistic event which was forecasted ahead, *scoring rule* was defined [2]. Moreover, it binds the assessor to make a careful prediction and hence truthfully elicit his/her private preferences. Which is why, *scoring rule* has been applied successfully while truthful incentive designing in diverse applications such as voting rules.

Household devices such as Roomba vacuum cleaners, LG ThinQ smart oven [3] are some commercially available smart devices that can be controlled and monitored via smart-meter. Using such devices, consumers (actually a consumer agent, referred as CA hereafter, will be responsible to take such decision in conjunction with smart-meter) can respond to day-ahead dynamic pricing signal by effectively and intelligently managing and scheduling devices, thereby flattening out peak demand and achieving better resource utilization.

This paper presents a hierarchical scoring rule based payment mechanism for CA provided by the EP and GENCO in response to the dynamic day-ahead time dependent pricing. The consumers will be rewarded a discount on the price to measure up how well they predict the shifting the devices/loads towards the lower demand (lower price as well) periods. These rewards are again a fraction of the discount which were provided by GENCO to the corresponding EP depending on EP’s prediction of required energy demand. The reward mechanism is based on a strictly proper scoring rule. The scoring rule is chosen to reflect to work with contin-

uous variable (the normal distribution, as in the proposed method) and measure up how accurate the prediction could be. The Continuous Ranked Probability Score [4] possess such characteristics. EP will formulate an optimization problem total energy demand for its consumers and reports to GENCO. GENCO then run an optimization algorithm that will minimize the cost of providing rewards to EPs while satisfying EPs energy demand. Therefore, the reward is actually dependent on both the consumers’ prediction and EP’s optimization problem.

As a mechanism design to incentivize agents (both the CAs and EPs) for providing private probabilistic information accurately (truthfully) and to the best of their forecasting ability, scoring rule is being applied in this model. Interestingly, such scenario coincides with DSM strategy where consumer responses to demand by shifting their device to lower price periods. Therefore, EP incentivises consumers not only based on their prediction accuracy but also on the question of whether they shifted such loads to lower priced periods. 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 details flow of information and task assignments are pointed in Figure 1. As we can see, GENCO will send the price information as a signal to EP. The price signal is typically determined based on the generation costs of electricity.*¹ Although this model does not include the price determination mechanism, we assume that in dynamic pricing environment, the signal follows the demand. Which is, the price is higher when the demand is higher and its lower when demand is lower. The price signals are then conveyed to CAs via EPs. One thing can be noted that, one EP can provide energy to one or more consumers while one GENCO can also serve one or more EPs. Since, this model assumes a dynamic “day-ahead” pricing signal, CAs receive their prices one day in advance. Therefore, CAs can schedule their device usages for the upcoming day into the lower price periods. Lets say, the demand in each period i is D_i . The demand D_i in each period is assumed to be roughly the same each day due to repeated daily

Contact: Shantanu Chakraborty, Nagoya Institute of Technology, Naogya, scborty@gmail.com or shantanu.chakraborty@nitech.ac.jp

*1 In our model, we assume that GENCOs operate on multiple plants of different types, such as coal, hydro and nuclear. Therefore, pricing signal could be a function of statistical forecast of historical price and the amount the EP pay to buy the energy from generation companies.

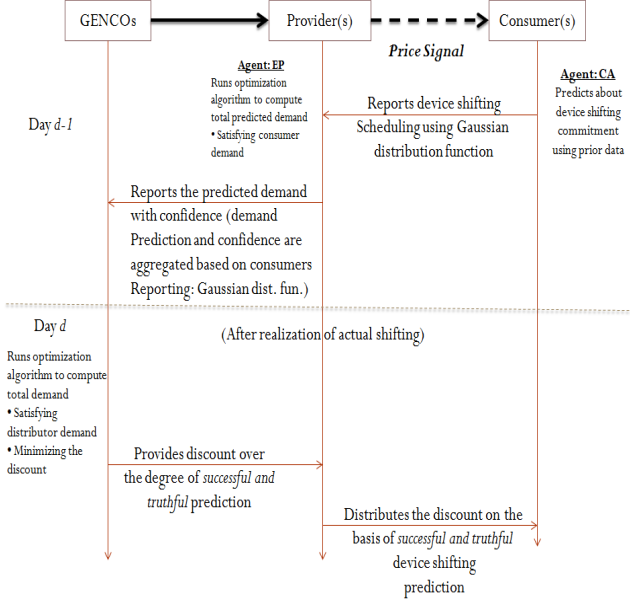


Figure 1: Information Flow of the GPC Model

patterns in electricity demands (e.g. period 1 has the same demand on Monday, Tuesday, etc.).

2. Continuous Ranked Probability Score (CRPS)

In order to rightfully incentivise the consumers on their prediction of device shifting; the continuous ranked probability score (CRPS) is applied [2]. CRPS is a strictly proper scoring rule that is used for continuous variable since, the traditional forms of proper and strictly proper scoring rules are usually not work with continuous variables. In the proposed method, Gaussian Distribution is used to model the consumers device shifting prediction and associated confidence. The usage of CRPS is investigated before in distributed power system operation to rightfully score the distributed energy resource(s). CRPS is able to measure the closeness of the prediction. Since, every device has different priority level of usage, we impose some weights over devices and calculate the actual weighted average of cumulative error as presented in Eq. (1)

$$\delta_u = \frac{\sum_{d=1}^{DV_u} \left(W_d \left| \frac{P_d^a - P_d^p}{P_d^p} \right| \right)}{\sum_{d=1}^{D_u}} \quad (1)$$

where P_d^a and P_d^p describe the prices of energy when the devices are operated at hours a (actual) and p (predicted). DV_u is the set of devices for CA, u . Lets assume, each CA, u reports its relative prediction error in a form of uncertainty over it, represented by *Gaussian Distribution Function* $\mathcal{N}(\mu = 0, \sigma_u^2)$. The reward score is therefore, generated by CRPS for that particular u is defined as Eq. (2)

$$CRPS(\mathcal{N}(\mu = 0, \sigma_u^2), \delta_u) = \sigma_u \left[\frac{1}{\sqrt{\pi}} - 2\varphi\left(\frac{\delta_u}{\sigma_u}\right) - \frac{\delta_u}{\sigma_u} \left(2\Phi\left(\frac{\delta_u}{\sigma_u}\right) - 1 \right) \right] \quad (2)$$

where the probability density function and cumulative distribution function for *Gaussian Distribution Function* are denoted as φ and

Φ , respectively. The notation $CRPS(\mathcal{N}(\mu = 0, \sigma_u^2), \delta_u)$ can be simplified using $CRPS(\sigma_u^2, \delta_u)$.

2.1 Truthfulness of Agents: CA and EP

However, predicting correctly about the device shifting schedule will not necessarily incentivize the CA to truthfully report its intentions regarding device shifting. For instance, a CA can misreport about shifting period of a particular device (or group of devices) to a higher priced period while in actual it shifts the device in a lower priced time. Therefore, although the CA will lose the some discount by incorrect prediction, it will gain benefit by shifting device(s) in lower priced period. In order to incorporate such scenario and strictly incentive the CA for reporting its true prediction, the scoring rule needs to be revised. Assuming the price curve follows the demand curve, the scoring rule (SR) is defined as following

$$SR = \begin{cases} CRPS & \text{if } (P_d^a - P_d^p) \geq 0 \forall d \in DV_u \\ 0 & \text{Otherwise} \end{cases} \quad (3)$$

This above function ensures that any misreporting by CA will generate a 0 score. For example, consider a case where a CA wants to use a device at period 1 and misreports that s/he will use it at period 2 (which is a higher priced period than period 1). Therefore, although s/he gets a less score for misreporting, it would appear that s/he will be compensated by lower price in period 1. But according to Eq. (3), it will get 0 discount. Hence, any CA who misreports of its true intention about shifting any device, will get no discount. CRPS is a strictly proper scoring rule that also ensures the truthfulness of the reporting [2]. The proposed scoring rule (Eq.(3)) also possesses the strictness property of CRPS since its internal mechanism also based on CRPS. Therefore, the proposed scoring rule is also truthful. Figure 3 shows the realization of scoring factors for different errors and confidence level. As pointed out before, the CAs will report their predictions of device usage in the mean of relative error (Eq. (1)) aggregated over all devices. Since, the CAs are aware of the scoring system used by the EPs, they have the liberty to choose associated confidence level (i.e. the sigma; σ). From the graph presented in Figure 3, it is important to notice that,

- when a CA is highly confident about its prediction (i.e. $\sigma_u = 0$); highest score is rewarded only when the realized absolute error is zero
- when the realized error is relatively higher, the CA will be benefitted to report lower confidence (i.e. higher values of σ)
- most importantly, CAs do not know the exact shape of the function when it declares the prediction, since the actual error only realized when the event occur

However, the CA has ideas how it will be scored. For instance, if it is likely to make a larger error, it implicitly chooses the function that will penalize it lower by reporting larger σ . On the other hand, if it is confident of its prediction accuracy, it will report a higher σ . By this way, we ensure CAs to report truthfully about their prediction intentions. Moreover, our model assume no *collusion* between the participating agent devices (CA and EP). As we

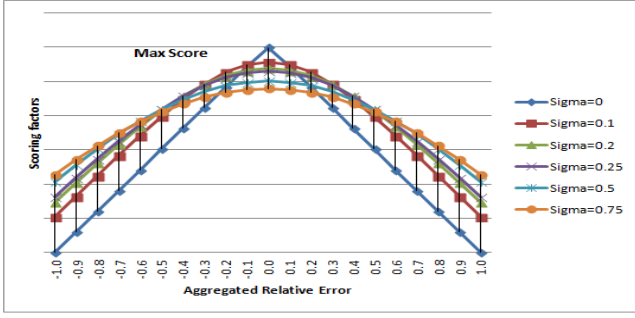


Figure 2: CRPS scoring mechanism for different errors

mentioned (and will show in later section), the prediction that EP makes regarding the aggregated energy requirement for its CAs, does not involve any imposition or disturbance towards CAs' device prediction. Rather, EP uses CAs' intentions as a base to report its prediction. Therefore, EP also exhibits the *truthfulness* property. So, the agent devices (CA and EP) used in this model are *truthful* and *non-collusive*.

2.2 GENCO and EP: Cost Optimization

Based on the device shifting prediction of CAs, EP will try to produce a *potential reward* (pr) which is actually based on the *shifting probability* of a particular device by the amount of shifting. In ideal case, where CA's device commitment prediction coincides with the actual one, there will be no shifting. Taking such scenario in mind, the *shifting probability* (SP) function is chosen to be concave and assumed to be increasing in pr and decreasing in shifting time t . The total cost of offering *potential reward* by summing up the demand shifted into period i is calculated as,

$$X_{ep} = \sum_{i=1}^N pr_i \sum_{u=1}^U \sum_{k \neq i} \sum_{j \in DV_u^k} e_j SP_j(pr_i, |k - i|) \quad (4)$$

EPS is the set of EP registered to buy energy from that GENCO. The cost of meeting consumers demand at period i , therefore, is

$$X_{genco} = \sum_{m=1,2} c_{im} [Y - C_{im}]^+ \quad (5)$$

The final optimization problem is defined as

$$\begin{aligned} \min_{pr} \quad & [X_{ep} + X_{genco}] \\ \text{s.t.} \quad & pr \geq 0 \end{aligned} \quad (6)$$

The discount EP will receive for their truthful prediction is

$$Discount_{EP} = \frac{(\sum_{i=1}^N pr_i) * CRPS(\sigma_{EP}^2, \delta_{EP})}{\sum_{EP \in EPS} CRPS(\sigma_{EP}^2, \delta_{EP})} \quad (7)$$

The scoring factor for u at period i is therefore, defined as

$$sf_u^i = \frac{\text{revenue}(\text{discount}_{EP}) * SR(\sigma_u^2, \delta_u)}{\sum_{u \in EP} SR(\sigma_u^2, \delta_u)} \times pr_i \quad (8)$$

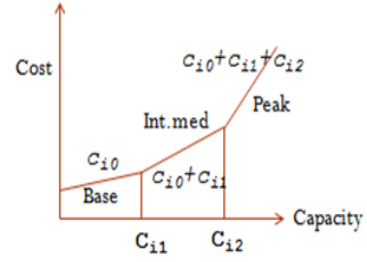


Figure 3: Piecewise linear cost model for base-, intermediate- and peak- load demand

3. Agent Simulation

In this section, some data analysis and preliminary simulation results are presented in order to verify the feasibility of the hierarchical scoring rule based pricing mechanism as well as to demonstrate the ability to reduce GENCO's cost of electric generation and flatten electric usage over some periods. For scalability we assume 1 GENCO entity which supplies energy to 10 electricity providers (EP). Which in turn serves 100 consumers each. However, the initial simulation is limited to 1-GENCO, 1-EP and 1-consumer model to elaborate the models' validity. The real parameters are based on Ontario Independent Electric Operator ([5]). The base-load plant in Ontario is hydroelectric; (assume 60% are base-load plants). The production capacity of each plant is taken as constant across different periods of a day for the purposes of simulation. The intermediate-load consists of coal (operating at 20% efficiency, as is consistent with IESO) and the remaining hydroelectric plants. Finally, the peak plants are gas turbines, which are the most expensive to operate. The slopes of the cost functions for base-, intermediate- and peak-load plants (refer to Figure 3) are taken from the production estimates reported in literature. The marginal costs of moving from intermediate- to peak load and base- to intermediate-load plants are calculated to be \$62.46/MWh and \$18.54/MWh respectively. Since its a GW based power system, the system data is effectively scaled down to provide simpler simulation conditions. The prices are also equivalently scaled into kWh level.

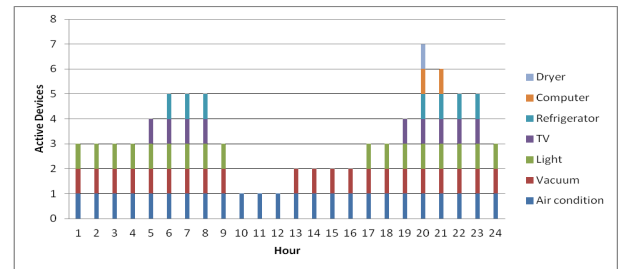


Figure 4: Hourly active devices for a single consumer in a 24-hours period after running smart pricing scheme

Assuming the electricity usage of a single consumer, Figure 4 presents the periodically expected device scheduling after applying the smart pricing scheme. While the quantitative results of these simulations will vary from market to market, the qualitative results suggest that smart pricing can indeed help GENCOs and

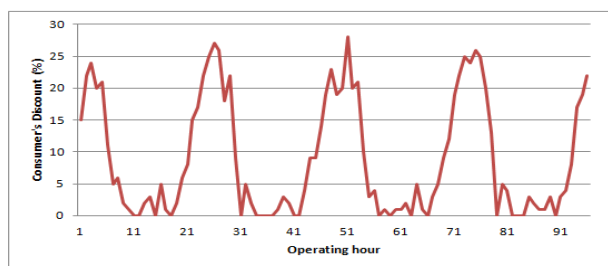


Figure 5: Discount provided to a single consumer for 96 hours. Total energy consumed 142.1 kWh.

EPs to even out consumption over the day and reduce the energy requirements from peak-load plants. Scrutinizing the cyclic electricity consumption pattern, it can be shown that for four consecutive days of energy consumption of 1 consumer reported is 142.1 kWh. However, before using the reward based pricing scheme, the total consumption recorded for a single consumer was 170.35 kWh (based on the single household consumption determined according to the data presented in [5]). Therefore, for a single consumer, the proposed scoring rule based reward scheme can reduce energy consumption down to 20%.

Figure 5 shows the rewards corresponding to the same energy consumption pattern as discussed in previous paragraph. It is noted that the rewards (discounts) are roughly cyclical, as might be expected. If we check the pattern, it is clearly seen that, in case of peak demand hour, the reward is minimum which states the fact that, it becomes difficult to make an accurate prediction in peak hour. Figure 6 depicts the effect of smart pricing scheme on pricing. We can see that, a CA can effectively reduce payment towards EP if it truthfully reports about its device scheduling on the basis of the day-ahead price signal and shifts them in lower priced period. To provide the scalability of the proposed method, Figure 7 is presented. It shows effect aggregated over 1000 consumers (1-GENCO, 10-EPs and 1000-consumers). It is noted that the peak-to-average (P2A) ratio of the consumption pattern before using scoring rule based smart pricing is 2.55 while it comes down to 1.91 when using the proposed pricing scheme. Qualitatively speaking, the P2A ratio is down by approximately 25%. Therefore, the proposed scheme works better when the number of consumers is higher. So, it can be said the method is practically viable and scalable. Moreover, such measure reflects the fact that the strictly proper scoring rule based reward mechanism is able to flatten the load demand.

4. Conclusion

This paper introduces a new smart pricing scheme considering a model consists of generators, provider and consumers. The formulations are carried by devising a truthful mechanism for both consumer and provider entities where they will report their true intentions regarding device scheduling and energy demand, respectively. The scoring system (facilitating *Continuous Ranked Probability Score*) is designed such a way that, it will force consumer agents to report their true beliefs towards providers. On the other hand, provider agents themselves are incentivised to report the energy demand to generation companies (GENCO) truthfully to get a discount over price. The conducted simulation results

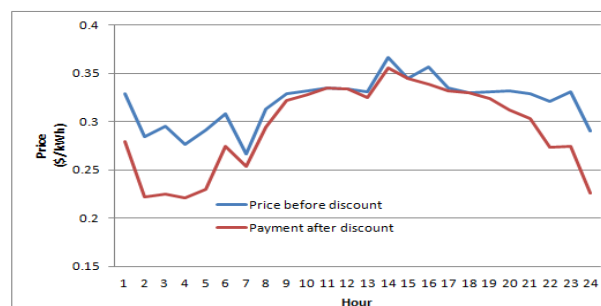


Figure 6: The price curve Vs. the payment which occurred before and after applying smart pricing scheme. This price signal is taken from 1st March, 2010.

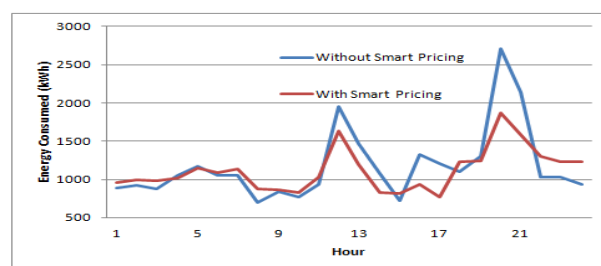


Figure 7: Energy usage before and after using of scoring rule based smart pricing; aggregated over 1000 consumers

show that, the proposed smart pricing scheme is able to reduce the total energy consumption as well as consumers payment towards providers. Therefore, consumers are benefitted since they paid less than the actual price and we have a cleaner environment with reduced energy production. As a future study, we will try to model the device sensitiveness towards scheduling and apply such mechanism for higher scaled smart power system.

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