# DEMAND RESPONSE PILOT EXPERIMENT AND ITS EVALUATION ON RESIDENTIAL AND SMALL COMMERCIAL & INDUSTRIAL CUSTOMERS: A KOREAN CASE

Dongsik, Jang
KEPCO, Korea
yojian2@kepco.co.kr

Sun-hee, Lee
KEPCO, Korea
sun7829@kepco.co.kr

Jiyong, Eom
KAIST, Korea
eomjiyong@kaist.ac.kr

Changhoon, Shin
KEPCO, Korea
hoony1968@kepco.co.kr

## ABSTRACT

*To expand demand response(DR) program to residential and small commercial & industrial (C&I) customers, KEPCO implemented peak time rebate(PTR) pilot study across summer and winter days in 2017 with more than two thousands of customers. The results of experiments have confirmed that PTR program is sufficiently cost-effective and sustainable to the utility as well as the whole society. In this study, models to quantify economic impacts of DR program are developed and applied to PTR experiments. Features of experimental design and some informative findings of Korean PTR pilot study for residential and small C&I customers are described and discussed in this paper.*

## INTRODUCTION

Since the first deployment time of use (TOU) tariff to its large industrial customers in 1977, KEPCO (Korea Electric Power Corporation) has expanded its TOU tariff to large commercial and educational customers in the continuation with the investment on AMI installation. However, residential and small C&I customer still do not have the option to choose time varying tariff. With the widespread deployment plan of AMIs to all the residential and small C&I customers by 2020, the Korean government and KEPCO are preparing to implement time varying tariffs to these customer sectors and planning to test several pilot experiments to devise more robust tariff design.

As the first attempt to deploy time varying tariff to small I&C and residential customers in Korea, the primary research question of KEPCO PTR pilot experiment was to find out whether the dynamic pricings of electricity are applicable to Korean customers with small electricity consumption. Even these pricings are widely implemented and expected to be the default tariffs in the near future across some developed countries, there are still concerns among many stakeholders in Korean electricity industry. Some of them are not sure that price signal is enough to motivate customers to change their peak use behaviours since the average electricity price of Korea is lower than those of many OECD countries. Others argue that demand response potential of these customer sectors is not large enough since the average electricity consumption of a customer is small. In addition to these, the issues regarding customer awareness to time-varying tariffs of electricity are assumed to a fundamental obstacle to be verified for the successful deployment of dynamic pricing.

Therefore, the objectives of KEPCO PTR pilot study were to address the following research questions.

- Are time-varying tariffs applicable to Korean residential and small C&I and customers? If so, how are their DR impacts?
- What makes a difference of DR impacts among customers? What is the most valuable customer segment for DR program marketing and recruitment.
- Impacts of parameters such as temperature, income, residence type, business type, and customers' energy consumption preference
- What are the elasticities of price signal in individual and aggregated customers? How much the DR impacts will be varied with price signal change?
- Will customers be satisfied with participation? What are the administrative tactics in enrolment, education, notification, feedbacks and so on?

## RESEARCH DESIGN AND EXPERIMENTS

### Pilot Study Schedule and Timeline

In March of 2017, KEPCO developed demand response management system (DRMS) for pilot experiment with functions of customer enrolment, DR event notification, one-hour interval metered data acquisition, PTR incentive evaluation and settlement, and customer-feedback. Before customer recruitment, there were several focus group interviews (FGIs) to probe the critical issues around electricity consumption and demand response behaviours. Survey design and questionnaire development followed using FGI results. Almost 2,000 customers were targeted by the stratified random sampling and recruited from May to July in 2017 with additional 1,000 customers for control group. With a condition of enrolment, all the participating customers were required to complete pre-enrolment on-site survey.

The first summer PTR event was called on August 9 in 2017. After that, there were a series of nine events followed through September. Participants received DR event feedbacks with the calculated electricity reduction in kWh and incentive to be paid within two working days after each event via mobile phone SMS (small massage service). Customers who have completed the whole summer DR events got on-site ex-post survey regarding summer DR behaviours, satisfaction, DR understandings and etc.

Winter PTR pilot experiments began from January 2018. KEPCO recruited additional two hundred customers to make up for the drop-outs at summer experiment. Churn rates of participants in summer were about 5% at both residential and small C&I customer segment. In winter events, KEPCO provided, as default information service, smart phone application to all participants which covers bill information, hourly electricity usage, participation records, sum of incentives to be paid, and tips for effective peak reduction. To study the effects of neighbouring customers' DR behaviour information and settlement rule change to free rider mitigation in PTR experiment, KEPCO divided participants into three groups. A total of nine winter PTR events were called during winter until the end of February.

## Experimental Treatments

The incentive for peak reduction was set to 0.89$/kWh. The default treatment to all participants, as many previous cases [1], was the day-ahead notification of DR event and measurement and verification(M&V) of peak reduction using pre-defined customer baseline (CBL) method. In addition to the default treatment, KEPCO PTR examined information effects of electricity rate in summer. The effects of neighbouring customers' DR behaviour information and settlement rule change to free rider mitigation were also tested at the winter PTR events.

In summer, customers were divided into two treatment groups. The first one was the default treatment group and the second one was electricity rate information treatment group. Since the benefits of PTR peak reduction are bill saving as well as incentive payment, participants in the second treatment group were expected to be in favour with this information and more motivated to participate in. These effects were expected to be more distinct to residential customers because they are put levy on three-tiered increasing block pricing.

For the winter PTR events, KEPCO provided the smart phone application to all participant. By accessing to this application, customers could find their bill information, the average hourly use of electricity for recent days, their PTR participation history and incentives to be paid, and tips for effective peak reduction. Participants in winter were categorized into three groups. As with summer PTR, the first one was default treatment group. The difference was whether the smart phone appliance was provided or not. The second treatment group received average peak reduction in kWh of customers with similar electricity usage patterns in their event feedback message. In customer behavioural science, it is known that a person tends to be more motivated when they get informed of neighbours' behaviour [2]. The second treatment was to examine these observations are also applicable to DR experiment. The third treatment group was designed to test the effects of settlement rule change to free rider mitigation. Due to biased estimation of CBL, estimation error itself, and asymmetric payment structure of PTR, it is often argued that PTR demand response is not sustainable nor cost-effective since it has a tendency of excessive payment to participants, resulting in free riders [3]. Participants in this group were ruled to be paid with their seasonal incentives by comparing cumulative CBL and peak usage instead of individual CBL at each event.

**Table 1. Treatment Groups in KEPCO PTR Pilot**

| Season | Group | Treatment |
|---|---|---|
| Summer | Default (Treat1) | - Day ahead alert |
| | Rate Information (Treat2) | - Day ahead alert + Electricity rate information |
| Winter | Default (Treat3) | - Day ahead alert + Smart Phone Application |
| | Neighboring Information (Treat4) | - Day ahead alert + Smart Phone Application<br>- Average peak reduction information of similar usage pattern cluster |
| | Settlement Rule Change (Treat5) | - Day ahead alert + Smart Phone Application<br>- Penalties if peak use > CBL |

Since the national demand of electricity in Korea has seasonal differences between summer and winter, KEPCO PTR study also applied different window of event hours with seasons. In summer, the peak period for summer PTR events was determined to set to start at 1:00 p.m. with length of 4 hours. However, since there are two peaks in the morning and the early evening within a day in winter, the peak period of residential customers was designated to begin at 5:00 p.m. and end at 8:00 p.m. The peak period for small C&I customers was set to be in the morning from 9:00 a.m. to noon with three hours.

# ANALYTICAL METHODOLOGY

## Specifications of Impact Evaluation

To evaluate the DR impact of experiment on peak hours, an econometric model is used to estimate the average treatment effect (ATE). The basic model captures this 'experiment' effect, as well as the effect of PTR events.

$$y_{it} = (\beta_0 + \beta_1 T1_i + \beta_2 T2_i) \cdot Exp_t + (\gamma_0 + \gamma_1 T1_i + \gamma_2 T2_i) \cdot Event_t + \theta X_{it} + \Pi_t + \alpha_i + \varepsilon_{it} \quad \text{(eqn.1)}$$

where the first term is the experiment effect, and the second term stands for the PTR event effect. The third term is a set of control variables and the forth term is time dependent variables, such as cooling degree day, humidity, hour-of-the-day dummies, month-of-the-year dummies, and hour-of-the-day times experiment dummies. The fifth and the last term are the customer-specific fixed effects and random error, respectively. This model is then extended to estimate possible moderation effects such as weather conditions (cooling degree hours; CDH), knowledge about electricity tariff (high, med, and low), the number of events experienced), consumption scale (contracted kW and monthly kWh) and so forth.

## Demand Model for Price Elasticities

The demand model represents the customers' electricity demand to electricity price change, controlling for other demand shifter, such as weather, socioeconomic and demographic factors. The estimated price elasticity of electricity demand is used as the primary input to develop price-based DR programs, such as PTR and TOU.

The hourly electricity demand models for the residential customers and small C&I customers in this study are given eqn2 and eqn3, respectively.

$$log(Use_{it}) = \alpha_i + \beta_1 log(Price_{it}) + \gamma_1 cdh6_t + \gamma_2 hdh6_t + \gamma_3 humid_t + \sum_j D_{month}[\delta_{1j} + \delta_{2j} D_{year(2016)}] + \delta_3 D_{holiday} + \mu_{hwd} + \varepsilon_{it} \quad \text{(eqn.2)}$$

$$log(Use_{it}) = \alpha + \beta_1 log(Price_{it}) + \gamma_1 cdh6_t + \gamma_2 hdh6_t * D_{heating} + \gamma_3 sun_t + + \sum_j D_{month}[\delta_{1j} + \delta_{2j} D_{year(2016)}] + \delta_3 D_{holiday} + \mu_{hwd} + \sum_k \sigma_k D_{class} + \theta_{1i} employee_i + \theta_{2i} floor.area_i + \theta_{3i} bizhour_i + \theta_{4i} bldgyear_i + \theta_{5i} sales_i + \theta_{6i} appliance_i + \varepsilon_{it} \quad \text{(eqn.3)}$$

A host of control variables are employed for evaluation. First, given that there is considerable heterogeneity in electricity consumption patterns between business types [4], small C&I demand model controls for business-type specific fixed-effects. Second, consistent with most previous studies on residential and commercial customers [5], the model controls for weather conditions, in terms of CDH or heating degree hours (HDH), humidity and the amount of sunshine. Third, stated monthly incomes and stated monthly sales are employed as control variables for the C&I customers. Fourth, control variables as floor area, ownership of electric heating system, and building age are also included as indicating the effect of buildings characteristics. Fifth, as measures of the scale and intensity of business activity that may affect electricity consumption during the peak hours, the number of employees, daily business hours, and appliance ownership are introduced [6] Last, hour-of-the-day fixed effects during weekdays ($\mu_{hwd}$) are used to capture time-pattern of business activities during the days.

## Enrolment Prediction and Customer Preference

Discrete choice models elicit preferences for individual attributes that characterizes a particular product or service, rather than preferences for the product itself, based on stated or revealed choices made by the consumers in response to a series of choice situations each with countable but mutually exhaustive options [7].

A nested logit (NL) choice model, which is an extension of the simple multinomial logit model, is chosen because it allows to combine qualitatively similar alternatives together using a nested choice structure. By doing so, small differences in product attributes (e.g., different costs of two identical services) would not have a significant influence on the substitution between different categories.

NL choice modeling approach is consistent with the perspective of the technology adoption theory, in which consumers' intent-to-use of new energy services involves two distinct processes of cognition and being affective [8]. To characterize preference of the participants based on survey data, two-layered nested structure is used. The upper nest corresponds to the *cognition process* of the technology adoption theory, in which a household chooses between adopting new electricity service plans (ESPs) and remaining with the status quo. The upper-nest decision would be made based upon the household's understanding of the most preferred option among the new ESP in the lower nest, which concerns the affective process. To capture unobserved heterogeneity relevant to consumer choices, willingness-to-pay (WTP) space model is also developed and tested.

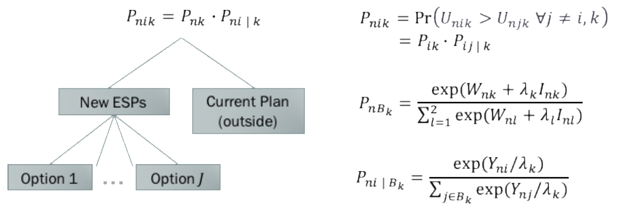


**Figure 1. Nested Logit Model for Predicting Enrolment**

# RESULTS AND DISCUSSION

## Demand Response of Residential Customers

The summer PTR experiment examined the impact of the PTR events (Treat1) and the role of rate information (Treat2). Analysis indicates (i) the treated customers reduced hourly electricity consumption by about 3~6Wh (1.0~1.5%) on non-event days during the program, but they curtailed more deeply during the PTR event hours by about 5~13Wh (2.8~4.1%); (ii) customers in Treat1 curtailed more during the program period than consumers in Treat2, while customers given with additional rate information reduced more in the PTR event hours than the customers given only with event notices; (iii) there was learning in demand response over the PTR events; and (iv) prior knowledge about tariff and peak time positively moderated PTR response of the Treat1 consumer while the knowledge did not made clear difference to Treat2 consumers.

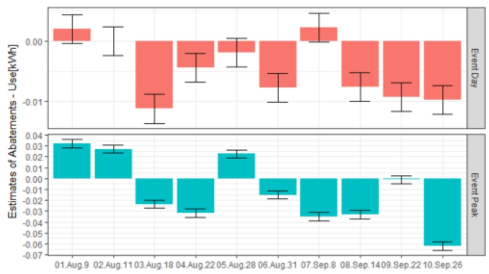


**Figure 2. ATE of Residential Customers for Each Summer PTR Event**

The winter PTR experiment consisted of three types of treatment to examine the impact of the PTR events (Treat3), the impact of providing neighboring information (Treat4), and the impact of settlement rule change (Treat5). Analysis results show (i) Treat3 and Treat5 customers presented an overall decrease in non-event day electricity consumption by 7-16Wh (2.9~3.3%) and 19Wh (2.6%) respectively; (ii) customers in Treat4 and Treat5 curtailed event-hour electricity consumption on average by 19Wh

(5.2%) and 20Wh (6.5%), respectively, while Treat3 consumers reduced 18-26Wh(6.0%); (iii) Treat5 slightly outperformed the conventional incentive scheme, while customers in Treat4 underperformed; (iv) all treated groups in the winter experiment gradually improved the curtailment of non-event day electricity consumption after the onset of the program, but event-hour learning effect was not identified.

Interestingly, residential customers were observed to abate their electricity consumption by 3~6Wh (1.0~1.5%) on non-event days during summer experimental period. It should be noted that since monetary incentive was based on the individuals' CBL, the consumption reduction in non-event days during the experiment would not be the best strategy. The curtailment of electricity consumption on the event hours gradually increased as PTR event repeated. It seems that learning in demand response is occurring in the treated households. It is also observed that customers reduce their electricity consumption much earlier than the start of the event hours. They first reduce their consumption at the time of receiving SMS notification (3:00 p.m. a day ahead) and then a few times before the event hours start. That is, demand response to PTR events is not made precisely during the targeted hours. Instead, more-than-a-day-long demand response around the event hours is made by the treated customers. Prior curtailment of electricity load to PTR events is also observed at small C&I customers.

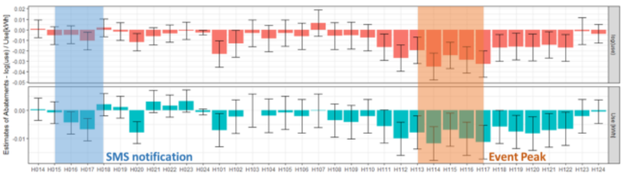


**Figure 3. ATE during 34 hours after day-ahead event notification**

The panel regression revealed the price elasticity of hourly electricity demand is -0.13 and statistically significant which are within the range of elasticity estimates reported in the literature.

## Demand Response of Small C&I Customers

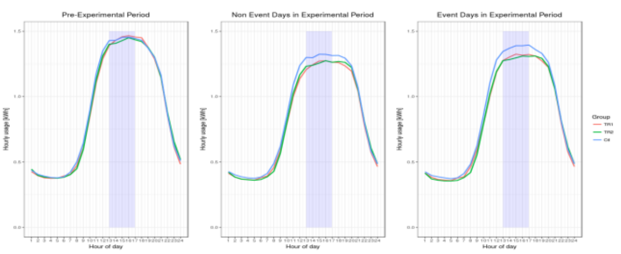


**Figure 4. Load Patterns of Small C&I Customer for Summer PTR**

For small C&I customers, analysis results of summer PTR indicate (i) the treated customers reduced hourly electricity consumption by about 23-40Wh on non-event days during the program, but they curtailed more deeply during the PTR event hours by about 27-50Wh; (ii) customers in Treat1 curtailed more during the program period than they did for the PTR event hours, while customers in Treat2 reduced more in the PTR event hours than they did during the program period; (iii) there was learning in demand response over the PTR events; and (iv) Treat2 customers reduced electricity consumption more than Treat1 in and around the event hours, although the former tended to compensate the foregone electricity use by consuming more at night than the latter.

The results of winter PTR experiment analysis show (i) Treat3 customers presented an overall increase in non-event day electricity consumption by 17-18Wh; (ii) customers in Treat4 curtailed event-hour electricity consumption on average by 40Wh, whereas Treat5 customers reduced on average by 84Wh; (iii) among customers in Treat4, those with relatively large daily consumption and large share of event-hour consumption exhibited greater demand response than those with small-to-medium daily consumption and small-to-medium share of event-hour consumption; (iv) the settlement rule change outperformed the conventional incentive scheme, with the former generating an event-hour reduction of about 84Wh and the latter of about 44Wh; and (v) learning in event-hour consumption reduction was observed over the course of our experiment.

Analysis of moderating factors indicates that a one degree-hour increase of the CDH leads to about a 64Wh increase in electricity consumption. The effect of HDH is estimated to be a 17Wh increase. As expected, the average treatment effect decreases with the increase of CDH and HDH leads to a 20-28Wh and 6-9Wh decrease in the average treatment effect, respectively. That is, electricity demand response becomes increasingly difficult as outdoor temperature goes to the extreme conditions. In addition, the marginal impact of HDH or CDH on the average treatment effect decreases as they increase.

The pooled OLS estimation conducted at the monthly and hourly level revealed (i) the price elasticity of monthly electricity demand is -0.18 and statistically significant; and (ii) the price elasticity of hourly electricity demand is -0.14 and statistically significant. Both of the estimates are within the range of elasticity estimates reported in the literature.

## Preference for Electricity Service Plans

The results of our NL model for residential TOU plans indicate that, all else being equal, households owning residences, living in smaller spaces, consuming more of electricity tend to have higher preference for TOUs over the default flat rate. The same trend holds for those with higher monthly incomes, higher educational degrees, and more knowledge on electricity bills. Also importantly, it was also indicated that prior experience with the summer PTR pilot is positively associated with the preference for

TOU plans, whereas the level of risk aversion is negatively associated with it. That is, for a broader deployment of TOU plans, prior exposure to a similar price-based demand response is important, and it is even more so for those with higher risk aversion.

The results of WTP space model with respect to TOU design attributes show that the opportunity of saving electricity bill by altering consumption patterns would be the main driver for subscribing the plans. And residential customers demand shorter peak hours preferably placed in the morning. This is intuitively reasonable because managerial attention is usually a costly resource for any electricity customers.

Regarding residential PTR plans, consistent with the case of TOU plans, customers owning residences, living in smaller spaces, consuming more of electricity tend to have higher preference for PTR plans over the default rate. In addition, households with higher monthly incomes, higher educational degrees, and more knowledge on electricity bills exhibit higher demand for the plans. However, in this case, the risk aversion does not play a statistically significant role in the demand for the PTR plans, probably because these plans do not involve financial penalties for over consumption although curtailment of electricity consumption is rewarded. WTP space model with respect to PTR design attributes indicates that, as one may expect, the households prefer to have a longer PTR event period, which is different from the case of TOU plans. More important finding is that the real-time information feedback works positively for the adoption of PTR plans, and it becomes more valuable as the length of peak period is shorter or trickier to handle.

**Table 2. Policy Simulation for Residential TOU Plans**

| TOU Attributes | Reference Plan | | Alternative 1 (Lower Peak) | Alternative 2 (Longer Peak/ Cheaper Feedback) | Alternative 3 (Longer/Higher Peak/ Cheaper Feedback) |
|---|---|---|---|---|---|
| Peak-to-Off-peak Ratio | 2.247 | | 2.121 | 2.247 | 2.472 |
| Peak Price (USD/kWh) | 0.201 | | 0.190 | 0.201 | 0.222 |
| Length of Peak (Hours) | 2 | 2 | 2/2 | 3/3 | 4/4 |
| Time of Peak | Morning | Evening | Identical | Identical | Identical |
| Cost of Feedback (USD/month) | 0.5 | | 0.5 | 0.1 | 0 |
| Feedback: Peak reminder | Yes | | Yes | Yes | Yes |
| Feedback: Real-time | Yes | | Yes | Yes | Yes |
| Expected subscription (%) | 81.7% | | 82.3% | 88.5% | 88.4% |
| Improvements (vs. Reference Plan) | - | | +0.6%p | +6.8%p | +6.7%p |

Using the identified preference results for residential TOU plans above, a set of hypothetical electricity service plan options are simulated to draw a way to improve the subscription rate of the TOU plans. Among the four alternative TOU scenarios, the reference TOU plan is characterized by two peak periods one in the morning and the other in the evening. 81.7% of the households are made better off with the reference plan and thus opt in. The next two alternatives with lower peak price (Alternative1) and lower peak price plus longer peak period (Alternative2), all are forecasted to increase the enrolment. Alternative3 reconciles a higher peak price with a longer peak period and cheaper service charges to result about the same enrollment rate as Alternative2.

## CONCLUSIONS & FUTURE WORK

KEPCO's PTR pilot study on residential and small C&I customers was the first attempt in Korea to implement the time-varying tariffs to these customer segments. However, the results of our analysis shows that they are within the range of outputs which have been observed at many previous PTR pilot experiments in other countries. Accordingly, these pricing schemes are expected to be sufficiently effective and sustainable to Korean society. Ex-post on-site surveys also confirmed these findings by showing that the majority of participants are satisfied with changing their electricity consumption behaviors on the peak hours and have an intention to continue the participation.

Even the primary results of our study are confirming, intuitive, and significant, it is necessary to investigate an experiment stretching over years to get more confirmative insights with certainty. The impacts of moderation variables including learning effect, rate information, and neighboring customer information are requiring to be studied in the future. In addition, impacts of demographic variables that are explaining the difference of participation among customers are still unclear to be investigated.

## REFERENCES

[1] S. George et al., 2013, *San Diego Gas & Electric Peak Time Rebate Baseline Evaluation*, FSC, USA, 46-50.

[2] J. LaRiviere et al., "Price vs nudges: a large field experiment on energy efficiency fixed cost investment", *Working Paper*. U. of Tennessee. 1-48

[3] E. Lee et al., 2018, "A two-step methodology for free rider mitigation with an improved settlement algorithm", *energies*. vol. 11, 3417.

[4] D. Jang et al., 2016, "Variability of electricity load patterns and its effect on demand response: a critical peak pricing experiment on Korean commercial and industrial customers", *Energy Policy*. vol. 88, 11-26.

[5] L.D. Taylor, 1975, "The Demand for electricity: survey", *Bell J. of Economics*. vol. 28, 681-685.

[6] Reiss and White, 2005, "Household electricity demand, revisited", *Review of Economic Studies*. vol. 39, 636-663.

[7] McFadden, 1974, *Frontiers in Econometrics*, Academie Press, New York, USA, 105-142.

[8] Wilson & Dowlatabadi, 2007, "Models of decision making and residential energy use", *Annual Review of Environmental Resources*. vol. 32, 169-203.