

# An Empirical Study of Real-time Feedback and Dynamic Pricing Effects on Electric Power Consumption *Field Experiment on a Remote Island in Japan*

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**Abstract:** The management of electric power demand is a key element in the creation of smart-energy communities. We are engaged in a field experiment with the participation of 51 households on Nushima Island, one of the remote islands of Japan, to study the effects of real-time feedback and dynamic pricing on electric power consumption using smart meters and tablet PCs. From the results of panel data analysis, we have found that these measures achieve an estimated saving of 22 percent in electric power consumption when the tablet PCs are accessed three times per day.

## 1 INTRODUCTION

Management of energy demand through feedback of power consumption and dynamic pricing will play a significant role in the creation of smart-energy communities that are both environmentally conscious and resilient to disasters.

These informational and economic interventions to households would contribute to climate change mitigation substantially through not only reducing the overall electric power demand but also controlling the demand so as to follow the renewable energy supply fluctuation.

Reductions of up to 20 percent in residential energy consumption have been reported through the technical innovations of real-time information feedback and dynamic pricing, with the actual energy savings achieved depending on the experimental conditions.

We have been focusing our efforts on the development of an effective feedback and pricing method for power demand management appropriate to regional conditions, and have been conducting a field experiment for this purpose on Nushima Island in Hyogo Prefecture, Japan.

In this paper, we outline the design of our

real-time feedback and dynamic pricing experiment and present the findings obtained from an empirical analysis.

## 2 LITERATURE REVIEW AND THE ORIGINALITY OF THIS STUDY

A number of field experiments have been conducted by various researchers aimed at estimating the effects of demand response by real-time information feedback and dynamic pricing.

### 2.1 Real-time Information Feedback Experiments

Faruqui et al. (2010a) conducted a review of a dozen utility pilot programs that were focused on either the energy conservation effects of in-home displays (IHDs) or demand-side management technologies. Their study revealed that the power demand of consumers who actively used an IHD was reduced by an average of approximately 7 percent excluding cases in which prepayment for electric power was

involved. They also found that consumers reduced their electric power consumption by double that amount when they were both using an IHD and in an electric power payment system.

On the other hand, Houde *et al.* (2013) found that access to real-time feedback resulted in a 5.7 percent average reduction in household electric power consumption, with significant declines continuing for up to four weeks. However, they only included few factors such as temperature and precipitation into their models.

Real-time information feedback has therefore been demonstrated to be an effective tool to reduce electric power consumption by 6 to 7 percent.

## 2.2 Dynamic Pricing Experiments

Faruqi *et al.* (2010b) reported the results of 15 experimental surveys showing that time-of-use (TOU) rates induce a drop in peak demand ranging from 3 to 6 percent and that critical-peak pricing (CPP) tariffs induce a drop in peak demand of between 13 and 20 percent.

On the other hand, Thorsnes *et al.* (2012) conducted an experiment on time-varying prices in New Zealand and found that, in winter, participating households reduced electric power consumption by at least 10 percent. They also pointed out that the response varied with house and household size. These pricing effects are dependent on peak/off-peak price differentials, with reductions ranging from several percent to 20 percent.

## 2.3 Originality of This Study

Having reviewed those existing studies, this study puts an emphasis on methodological development to achieve overall electric power demand reduction rather than aiming at peak cut or peak shift by using informational and economic intervention.

Additionally, this study takes into account a wide variety of factors that affect electric power consumption level: not only weather conditions such as temperature and wind speed but also the number of electric appliances in use and living conditions such as housing structures and electric power contact types.

Our model can take into account the impacts of various surrounding factors so as to estimate the real-time feedback and dynamic pricing effects more sharply than previous studies such as Houde *et al.* (2013).

## 3 METHOD AND DATA

### 3.1 Outline of the Experiment

Considering both the experiences in the previous experiments and the fragile condition of electric power supply on remote islands, we designed a field experiment on Nushima Island with the following objectives:

- 1) to estimate the effects of both real-time information feedback and dynamic pricing on electric power consumption;
- 2) to investigate the sustainable long-term effect obtainable by these measures in terms of climate change mitigation, rather than focusing only on short-term demand response;
- 3) to develop an effective pricing method in accordance with the daily fluctuations of solar photovoltaic power generation on the island.

With regard to item 3) above, the pricing signal may be reversed when compared with the usual practice of peak load pricing because the price on a hot and sunny day will be high.

This empirical study being carried out on Nushima Island is a three-year project that commenced in 2012. In that year, smart meters were installed in the dwellings of 51 households. In May 2013, tablet PCs were distributed to the participants to provide them with feedback on their electric power consumption. In addition, dynamic pricing was introduced on a trial basis in the summer of 2014.

#### 3.1.1 Real-time Feedback

We have presented three patterns of feedback information to the participating households related to their electric power consumption. Figure 1 shows the various types of information displayed on a tablet PC. Each household can view its electric power consumption and per-capita consumption in real time PC in Pattern 1. In Pattern 2, they can also compare their consumption with the average consumption of the participating households. Furthermore, in Pattern 3, a ranking of the levels of power consumption of the participating households is displayed.

Table 1 shows the schedule of the feedback patterns. The patterns were rotated monthly from Pattern 1 to Pattern 3 in succession until April 2014, and then remained in Pattern 3 from May 2014 onward in preparation for the dynamic pricing experiment in the summer. This was based on the principle that the effect of dynamic pricing would be

able to be assessed most clearly when the type of feedback information was fixed.

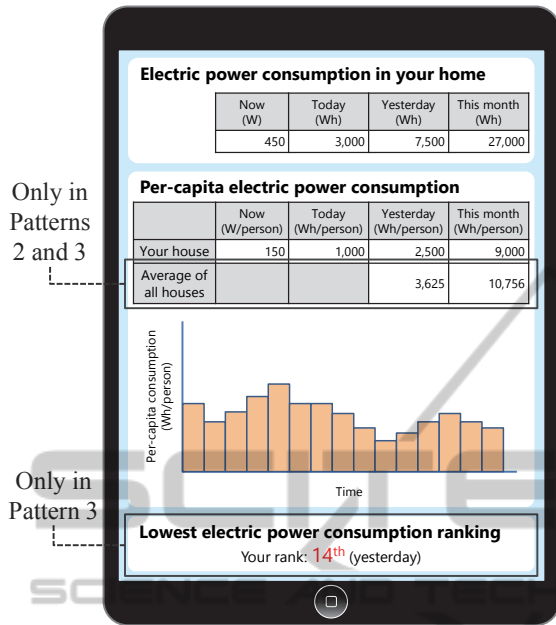


Figure 1: Information displayed on a tablet PC.

Table 1: Schedule of feedback patterns.

	Pattern			
	1	2	3	
2013	Jan.-Apr.			
	May	○		
	Jun.	○		
	Jul.		○	
	Aug.			○
	Sep.	○		
	Oct.		○	
	Nov.-Dec.			○
2014	Jan.		○	
	Feb.			○
	Mar.	○		
	Apr.		○	
	May-Oct.			○

### 3.1.2 Dynamic Pricing

The dynamic pricing experiment was implemented from August 26 to September 8, 2014. Each of the participating households was allocated 7,000 points at the beginning of the experiment, and points were deducted based on their electric power consumption. Participants could exchange the remaining balance of points into real money at the end of the experiment.

We prepared three types of deduction rates and changed the rate daily according to the weather forecast. The rate, calculated in terms of points/(kWh/person), was 20 when the weather forecast for both the preceding and current days included “sunny,” 30 when the forecast for either the preceding or current days included “sunny,” and 40 when the forecast for neither the preceding nor current days included “sunny.” The reason why the deduction rate on cloudy or rainy days was higher than on sunny days was that we assumed a smart-energy community where electric power is supplied by renewable energy such as solar power and energy stored in batteries. Energy stored in the batteries would decrease on cloudy or rainy days because the photovoltaic power generation system would produce less energy. Table 2 shows the daily weather forecast and the deduction rates during the period of the dynamic pricing experiment.

Table 2: Schedule of deduction rates.

	Weather forecast	Deduction rate [points/(kWh/person)]
Aug. 26		30
Aug. 27		40
Aug. 28		30
Aug. 29		20
Aug. 30		20
Aug. 31		20
Sep. 1		20
Sep. 2		20
Sep. 3		20
Sep. 4		30
Sep. 5		40
Sep. 6		40
Sep. 7		40
Sep. 8		30

## 3.2 Analysis Method

### 3.2.1 Panel Data Analysis

We have been conducting panel data analysis in this study to assess the effects of real-time feedback and dynamic pricing on the management of electric power demand. In view of the fact that power demand varies according to various factors,

including temperature, household size, and types of household electrical appliances used, the effects of feedback and dynamic pricing should be estimated separately from other factors that may have an influence on electric power consumption taking the diversity of the participating households into consideration.

### 3.2.2 Analysis of All Households

We performed an analysis of the daily electric power consumption of the 51 participating households. Equation (1) is the estimating equation used to determine the effects of real-time feedback and dynamic pricing on daily power demand. The equation defines daily electric power consumption in terms of an explained variable and four types of factors as explanatory variables; namely, factors related to the external environment, internal environment, feedback, and dynamic pricing. The formula was originally developed for this study based on the authors' investigations.

The external environmental factors refer to the weather conditions; namely, the cooling degree-hours, heating degree-hours, and daily mean wind speed. The cooling/heating degree-hours describe to what extent (in degrees) and for how long (in hours) the outside air temperature is higher/lower than a specific base temperature. The base temperature for cooling degree-hours was set at 24°C and that for heating degree-hours was set at 18°C.

The internal environmental factors were composed of the number of household members, air conditioners, refrigerators, and commercial freezers in the case of households engaged in fishery; whether all of the energy in a household was supplied by electricity; whether non-electrical heating equipment was used; whether the household was living in a timber house; and whether the targeted period was the summer vacation season.

The factors related to feedback consisted of the feedback pattern and the frequency of viewing electric power consumption on the tablet PC.

Finally, the factors related to dynamic pricing comprised three deduction rates according to the weather conditions.

We adopted a cross-sectional seemingly unrelated regression (SUR) model in order to take a large number of explanatory variables into consideration. The number of samples obtained excluding missing values amounted to 28,347, which were collected from the 51 households over a period of 664 days from January 1, 2013 to October 31, 2014.

$$\begin{aligned}
 EC_{i,d} &= C + \alpha_1 HH_{i,d} + \alpha_2 HH_{i,d}^{\frac{1}{2}} + \alpha_3 CDH_{i,d} \\
 &+ \alpha_4 CDH_{i,d}^2 + \alpha_5 HDH_{i,d} + \alpha_6 HDH_{i,d}^2 \\
 &+ \alpha_7 WS_{i,d} + \alpha_8 AC_{i,d} + \alpha_9 RF_{i,d} \\
 &+ \alpha_{10} CF_{i,d} + \alpha_{11} DUME_{i,d} + \alpha_{12} DUMK_{i,d} \\
 &+ \alpha_{13} DUMT_{i,d} + \alpha_{14} DUMV_{i,d} \\
 &+ \alpha_{15} DUM1\_1305_{i,d} + \dots \\
 &+ \alpha_{19} DUM1\_1403_{i,d} \\
 &+ \alpha_{20} DUM2\_1307_{i,d} + \dots \\
 &+ \alpha_{23} DUM2\_1404_{i,d} \\
 &+ \alpha_{24} DUM1\_1308_{i,d} + \dots \\
 &+ \alpha_{32} DUM3\_1410_{i,d} \\
 &+ \alpha_{33} \{ \ln(VC_{i,d} + 1) \times DUM1\_1305_{i,d} \} \\
 &+ \dots \\
 &+ \alpha_{50} \{ \ln(VC_{i,d} + 1) \times DUM3\_1410_{i,d} \} \\
 &+ \alpha_{51} DUM20_{i,d} + \alpha_{52} DUM30_{i,d} \\
 &+ \alpha_{53} DUM40_{i,d} \\
 &+ \alpha_{54} \{ \ln(VC_{i,d} + 1) \times DUM20P_{i,d} \} \\
 &+ \alpha_{55} \{ \ln(VC_{i,d} + 1) \times DUM30P_{i,d} \} \\
 &+ \alpha_{56} \{ \ln(VC_{i,d} + 1) \times DUM40P_{i,d} \}
 \end{aligned} \tag{1}$$

<i>EC</i>	Daily electric power consumption [Wh/day]
<i>C</i>	Constant
<i>HH</i>	Number of household members [persons]
<i>CDH</i>	Cooling degree-hours [degree-hours]
<i>HDH</i>	Heating degree-hours [degree-hours]
<i>WS</i>	Daily mean wind speed [m/s]
<i>AC</i>	Number of air conditioners [units]
<i>RF</i>	Number of refrigerators [units]
<i>CF</i>	Number of commercial freezers [units]
<i>DUME</i>	Dummy variable for households where all energy is supplied by electric power
<i>DUMK</i>	Dummy variable for use of non-electrical heating equipment such as a kerosene heater
<i>DUMT</i>	Dummy variable for living in a timber house
<i>DUMV</i>	Dummy variable for summer vacation season
<i>DUMX_Y</i>	Dummy variable for feedback period (X: pattern of feedback, Y: month)
<i>VC</i>	Daily frequency of viewing electric power consumption on the tablet PC [times/day]
<i>DUMZP</i>	Dummy variable for days of dynamic pricing (Z: deduction rate)
<i>α</i>	Partial regression coefficient
<i>d</i>	Date
<i>i</i>	ID number of each household

### 3.2.3 Analysis by District

There are five districts on Nushima Island, and the characteristics of and attitudes toward this experimental study differ among them. We therefore assessed the impact of real-time feedback and dynamic pricing by district. The analysis was performed using Equation (2).

Equation (2) has fewer variables than Equation (1) because it has constraints based on the cross-sectional sample volume for panel data analysis.

This analysis focused on feedback of the Pattern 3 type and dynamic pricing. We also adopted a cross-sectional SUR model here. The number of samples obtained excluding missing values was 3,396 in Minami District, 3,480 in Naka District, 4,424 in Kita District, 3,342 in Higashi District, and 2,591 in Tomari District.

$$\begin{aligned}
 EC_{i,d} &= C + \alpha_1 HH_{i,d} + \alpha_2 HH_{i,d}^{\frac{1}{2}} + \alpha_3 CDH_{i,d} \\
 &+ \alpha_4 CDH_{i,d}^2 + \alpha_5 HDH_{i,d} + \alpha_6 HDH_{i,d}^2 \\
 &+ \alpha_7 WS_{i,d} + \alpha_8 AC_{i,d} + \alpha_9 RF_{i,d} \\
 &+ \alpha_{10} CF_{i,d} + \alpha_{11} DUME_{i,d} + \alpha_{12} DUMK_{i,d} \\
 &+ \alpha_{13} DUMV_{i,d} + \alpha_{14} DUM3_{i,d} \\
 &+ \alpha_{15} \{\ln(VC_{i,d} + 1) \times DUM3_{i,d}\} \\
 &+ \alpha_{16} DUM20_{i,d} + \alpha_{17} DUM30_{i,d} \\
 &+ \alpha_{18} DUM40_{i,d} \\
 &+ \alpha_{19} \{\ln(VC_{i,d} + 1) \times DUM20P_{i,d}\} \\
 &+ \alpha_{20} \{\ln(VC_{i,d} + 1) \times DUM30P_{i,d}\} \\
 &+ \alpha_{21} \{\ln(VC_{i,d} + 1) \times DUM40P_{i,d}\}
 \end{aligned} \quad (2)$$

*DUM3* Dummy variable for feedback period in Pattern 3

### 3.3 Data

We are assessing the impacts of feedback and dynamic pricing on the actual electric power demand by using data collected via smart meters. Smart meters are also gathering data on the frequency of viewing power consumption feedback on the tablet PCs. Data regarding the external environmental factors for the present study were obtained or calculated from the Climate Statistics provided online by the Japan Meteorological Agency. Data on the internal environmental factors such as the number of electrical appliances were based on questionnaires targeting the participating households.

## 4 RESULTS AND DISCUSSION

### 4.1 Results of Dynamic Pricing

The average electric power consumption of the participating households during the period of the dynamic pricing experiment was reduced by 2.7 percent compared with the same period in the preceding year. Figure 2 shows the changes in power consumption compared with the preceding year by district. Reductions in power consumption were seen in all of the districts except Tomari, with the Kita District achieving the largest reduction.

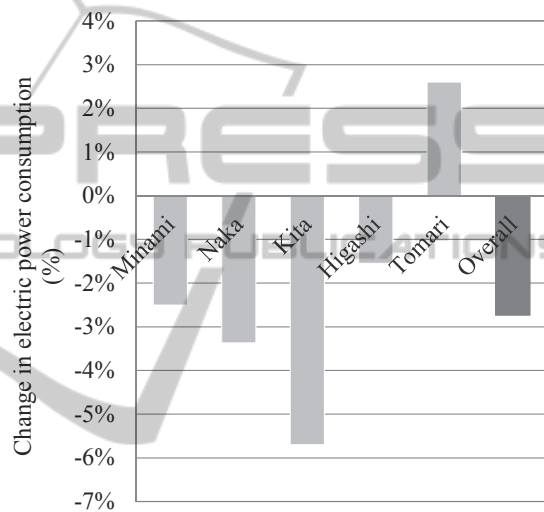


Figure 2: Changes in electric power consumption compared with the preceding year by district.

### 4.2 Results of Panel Data Analysis

#### 4.2.1 Analysis of All Households

From the results of the panel data analysis of all of the participating households, the adjusted R squared value was 0.9142 and the Durbin-Watson statistic was 1.183. As shown in Table 3, real-time feedback had the effect of reducing electric power consumption in many of the months studied, because the coefficients of *DUM1\_1305*, *DUM1\_1306*, *DUM1\_1309*, *DUM2\_1307*, *DUM2\_1310*, *DUM2\_1404*, *DUM3\_1311*, *DUM3\_1405*, *DUM3\_1406*, *DUM3\_1407*, *DUM3\_1409*, and *DUM3\_1410* are statistically significant at the 1 percent level and have negative value. The symbols \*, \*\*, and \*\*\* in Table 3 indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Additionally, the coefficients of the cross terms

Table 3: Main results of analysis of all participating households.

Variable	Coefficient	t value
<i>DUM1_1305</i> (*1)	-1,838 ***	-9.212
<i>DUM1_1306</i> (*1)	-2,632 ***	-12.06
<i>DUM1_1309</i> (*1)	-1,992 ***	-9.230
<i>DUM1_1312</i>	138.0	0.7339
<i>DUM1_1403</i>	-87.23	-0.693
<i>DUM2_1307</i> (*1)	-1,898 ***	-6.437
<i>DUM2_1310</i> (*1)	-2,267 ***	-14.51
<i>DUM2_1401</i>	343.3 **	1.961
<i>DUM2_1404</i>	-1,852 ***	-12.57
<i>DUM3_1308</i>	118.6	0.3208
<i>DUM3_1311</i>	-1,027 ***	-8.146
<i>DUM3_1402</i>	285.4 *	1.753
<i>DUM3_1405</i> (*2)	-2,510 ***	-16.72
<i>DUM3_1406</i> (*2)	-2,612 ***	-14.52
<i>DUM3_1407</i> (*2)	-1,623 ***	-6.625
<i>DUM3_1408</i>	-344.6	-1.296
<i>DUM3_1409</i> (*2)	-2,600 ***	-13.06
<i>DUM3_1410</i> (*2)	-2,662 ***	-15.32
$\ln(VC+1) \times DUM1_1305$	59.94	0.8199
$\ln(VC+1) \times DUM1_1306$	59.31	0.8148
$\ln(VC+1) \times DUM1_1309$	-151.4	-1.457
$\ln(VC+1) \times DUM1_1312$	661.9 ***	3.476
$\ln(VC+1) \times DUM1_1403$	601.3 **	4.175
$\ln(VC+1) \times DUM2_1307$	-497.9 ***	-4.127
$\ln(VC+1) \times DUM2_1310$	21.97	0.1480
$\ln(VC+1) \times DUM2_1401$	342.5	1.498
$\ln(VC+1) \times DUM2_1404$	949.6 ***	5.801
$\ln(VC+1) \times DUM3_1308$	-189.4	-1.251
$\ln(VC+1) \times DUM3_1311$	468.8 **	2.565
$\ln(VC+1) \times DUM3_1402$	646.4 ***	3.919
$\ln(VC+1) \times DUM3_1405$	805.6 ***	5.213
$\ln(VC+1) \times DUM3_1406$	-14.78	-0.1529
$\ln(VC+1) \times DUM3_1407$ (*3)	-640.4 ***	-4.173
$\ln(VC+1) \times DUM3_1408$ (*3)	-1,303 ***	-8.063
$\ln(VC+1) \times DUM3_1409$ (*3)	-382.4 ***	-3.384
$\ln(VC+1) \times DUM3_1410$ (*3)	-560.1 ***	-5.152
<i>DUM20P</i>	29.51	0.0766
<i>DUM30P</i>	281.1	0.9736
<i>DUM40P</i> (*4)	1,123 ***	4.998
$\ln(VC+1) \times DUM20P$	150.7	0.5276
$\ln(VC+1) \times DUM30P$	-123.2	-0.444
$\ln(VC+1) \times DUM40P$ (*4)	-1,049 ***	-3,653

between the frequency of viewing a tablet PC and the dummy variable for the feedback pattern are statistically significant at the 1 percent level and have negative value from July to October, 2014, which are indicated in (\*3) in Table 3. Those coefficients range from approximately -380 to -1,300.

However, particularly in the winter and spring seasons, the significant coefficients of the same cross terms are sometimes positive. It is considered to be difficult to reduce electric power consumption in winter, despite the fact that the actively participating households confirmed their

consumption level frequently via the tablet PCs. The differing effects between summer and winter may be related to consumers' perception gap between subjective savings and real savings, as reported by Attari et al. (2010).

On the other hand, only the coefficients of *DUM40P* and  $\ln(VC+1) \times DUM40P$  are statistically significant among the variables related to dynamic pricing, which are indicated in (\*4) in Table 3. The result in which *DUM40P* has a positive coefficient and  $\ln(VC+1) \times DUM40P$  has a negative coefficient indicates that households that viewed their tablet PC frequently reduced electric power consumption when the deduction rate was 40 points.

Table 4 shows the estimated effect of real-time feedback and dynamic pricing compared with the mean daily consumption of the participating households during the dynamic pricing experiment. Households viewing electric power consumption on the tablet PC three times per day are estimated to have reduced power consumption by 20.1 percent through real-time feedback and 2.1 percent through dynamic pricing.

Regarding the long-term effect of electric power consumption reduction by real-time information feedback, we confirmed almost the same level of coefficients of feedback pattern dummy variables between May/June/July/September/October of 2013 (*DUM1\_1305*, *DUM1\_1306*, *DUM2\_1307*, *DUM1\_1309*, *DUM2\_1310*: -1,838 to -2,632, which are indicated in (\*1) in Table 3) and the same months of 2014 (*DUM3\_1405*, *DUM3\_1406*, *DUM3\_1407*, *DUM3\_1409*, *DUM3\_1410*: -1,623 to -2,662, which are indicated in (\*2) in Table 3). At least for these two years, except in August, real-time information feedback was found to work continuously as an effective electric power demand reduction measure. These results are quite different from those of the previous studies such as Houde et al. (2013) that indicated significant reductions

Table 4: Estimated reduction rate achieved by feedback and dynamic pricing during the dynamic pricing experiment.

	Frequency of viewing tablet PC per day			
	0	1	2	3
<b>Real-time feedback</b>	-	-	-	-
<b>Pattern 3</b>	16.7%	18.4%	19.4%	20.1%
<b>Dynamic pricing</b>				
<b>Deduction rate: 40</b>	+7.2%	+2.5%	-0.2%	-2.1%

continued only for four weeks.

On the other hand, there was no distinct difference in electric power consumption reduction effects among the feedback patterns (Patterns 1 to 3) according to the coefficients of feed-back pattern's dummy variables (*DUM1*, *DUM2*, *DUM3*) in Table 3.

#### 4.2.2 Analysis by District

The estimation results obtained from the panel data analysis by district are shown in Table 5. The coefficients of the dummy variable for feedback in Pattern 3 and the cross terms between the frequency of viewing a tablet PC and the dummy variable for dynamic pricing when the deduction rate was 30/40 were statistically significant at the 1 percent level and had negative values in the districts of Kita, Naka, and Minami, which are indicated in (\*) in Table 5. These districts are ranked in the top three for reduction of electric power consumption, as shown in Figure 2. This indicates that households in the top three districts tended to reduce power consumption when the deduction rate was high.

Particularly in the districts of Minami and Naka, real-time feedback in Pattern 3 had the effect of reducing power consumption by 11.4 percent compared with the average consumption level of those districts.

Moreover, in Minami District, the frequency of viewing a tablet PC per day increased the power consumption reduction rate as the deduction rate increased, as shown in Table 6. The power consumption reduction rate ranged from 8.7 percent to 19.3 percent when the tablet PCs were accessed three times per day.

Table 6: Estimated reduction rate by dynamic pricing during the dynamic pricing experiment in Minami District.

Dynamic pricing	Frequency of viewing tablet PC per day			
	0	1	2	3
Deduction rate: 20	5.2%	-1.7%	-5.8%	-8.7%
Deduction rate: 30	0.9%	-6.0%	10.0%	12.8%
Deduction rate: 40	8.6%	-5.4%	13.5%	19.3%

## 5 CONCLUSIONS

This study investigated the effects of real-time information feedback and dynamic pricing on

Table 5: Results of analysis by district.

Variable	Coefficient	t value
<b>Minami District</b>		
<i>DUM3</i> (*)	-1,769 ***	-11.18
$\ln(VC+1) \times DUM3$	83.34	0.4733
<i>DUM20P</i>	763.3	1.188
<i>DUM30P</i>	133.4	0.3820
<i>DUM40P</i>	1,255 *	1.907
$\ln(VC+1) \times DUM20P$	-1,464 ***	-3.127
$\ln(VC+1) \times DUM30P$ (*)	-1,449 ***	-2.726
$\ln(VC+1) \times DUM40P$ (*)	-2,943 ***	-4.812
<b>Naka District</b>		
<i>DUM3</i> (*)	-1,747 ***	-7.213
$\ln(VC+1) \times DUM3$	-13.46	-0.1082
<i>DUM20P</i>	551.7	1.258
<i>DUM30P</i>	747.0	1.370
<i>DUM40P</i>	1,335 ***	5.247
$\ln(VC+1) \times DUM20P$	-450	-1.578
$\ln(VC+1) \times DUM30P$	-420	-0.6579
$\ln(VC+1) \times DUM40P$ (*)	-1,314 ***	-6.045
<b>Kita District</b>		
<i>DUM3</i> (*)	-520.6 ***	-3.324
$\ln(VC+1) \times DUM3$	204.5	1.700
<i>DUM20P</i>	136.8	0.3491
<i>DUM30P</i>	-27.76	-0.03656
<i>DUM40P</i>	408	0.8410
$\ln(VC+1) \times DUM20P$	-318	-0.5738
$\ln(VC+1) \times DUM30P$ (*)	-1,160 ***	-4.115
$\ln(VC+1) \times DUM40P$	25.50	0.06106
<b>Higashi District</b>		
<i>DUM3</i>	-98.05	-0.4563
$\ln(VC+1) \times DUM3$	-328.8	-1.344
<i>DUM20P</i>	932.5 *	1.857
<i>DUM30P</i>	847.6	1.301
<i>DUM40P</i>	573.9	1.540
$\ln(VC+1) \times DUM20P$	-262.7	-0.6315
$\ln(VC+1) \times DUM30P$	30.80	0.1016
$\ln(VC+1) \times DUM40P$	-536.8	-0.5428
<b>Tomari District</b>		
<i>DUM3</i>	727.3 ***	3.671
$\ln(VC+1) \times DUM3$	-41.71	-0.2359
<i>DUM20P</i>	-383.1	-0.5817
<i>DUM30P</i>	838.1 *	1.517
<i>DUM40P</i>	955.1	1.758
$\ln(VC+1) \times DUM20P$	239.7	0.3500
$\ln(VC+1) \times DUM30P$	-1,348 **	-2.198
$\ln(VC+1) \times DUM40P$	-667.0	-0.8523
	Adjusted R-squared	DW statistic
Minami	0.7377	1.007
Naka	0.7782	0.7443
Kita	0.9660	1.026
Higashi	0.6906	0.7322
Tomari	0.7951	0.9711

residential electric power consumption based on the results of a field experiment on Nushima Island in Japan.

We obtained several interesting findings, as follows:

- 1) Our estimate of the power demand reduction effects for all of the participating households revealed that real-time feedback achieved a reduction of 20 percent in electric power consumption and that the highest level of dynamic pricing also achieved a saving of 2 percent when the tablet PCs were accessed three times per day.
- 2) In two of the five districts, real-time information feedback showed a substantial power reduction effect of 11.4 percent. In one of these districts, the highest pricing resulted in a 19.3 percent reduction in residential electric power consumption when the tablet PCs were accessed three times per day.
- 3) The effect of real-time information feedback on electric power demand has remained at the same level for two years.
- 4) The real-time information feedback pattern caused no difference in terms of changes in electric power consumption.

Our findings would also be useful for demand-side management system design in residential smart grid that has been intensively developed in recent years by several researchers such as Liu *et. al.* (2014).

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## REFERENCES

- Attari, S., Dekay, M. L., Davidson, C. I., de Bruin, W. B., 2010. Public perception of energy consumption and savings. In *Proceedings of the National Academy of Science of the United States of America*; 107-37, 16054–16059.
- Faruqi, A., Sergici, S., Sharif, A., 2010a. The Impact of Informational Feedback on Energy Consumption—A Survey of the Experimental Evidence. In *Energy*, 35-4, 1598–1608.
- Faruqi, A., Sergici, S., Sharif, A., 2010b. Household response to dynamic pricing of electricity: A survey of 15 experiments. In *Journal of Regulatory Economics*, 38, 193–225.
- Houde S., Todd A., Sudarshan A., Flora J. A., Armet K. C., 2013. Real-time Feedback and Electricity Consumption: A Field Experiment Assessing the Potential for Savings and Persistence. In *The Energy Journal*, 34-1, 87–102.
- Japan Meteorological Agency, Climate Statistics [http://www.data.jma.go.jp/obd/stats/etrn/index.php?prec\\_no=63&block\\_no=1337&year=&month=&day=&view](http://www.data.jma.go.jp/obd/stats/etrn/index.php?prec_no=63&block_no=1337&year=&month=&day=&view).
- Liu Y., Yuen C., Huang S., Ul Hassan N., Wang X., Xie S., 2014. Peak-to-Average Ratio Constrained Demand-Side Management with Consumers Preference in Residential Smart Grid. In *IEEE Journal of Selected Topics in Signal Processing*. 8-6, 1084-1097.
- Thorsnes P., Williams, J., Lawson, R., 2012. Consumer responses to time varying prices for electricity. In *Energy Policy*, 49, 552–561.