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Tailor-Made Feedback to Reduce Residential Electricity Consumption: The Effect of Information on Household Lifestyle in Japan

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Abstract: Residential smart metering and energy feedback have attracted worldwide attention toward reducing energy consumption and building a sustainable society. Many theoretical studies have suggested the importance of personalized information; however, few feedback demonstrations have focused on household lifestyle. This paper presents a pilot program of energy feedback reports based on analytical methods to show the relationship between electricity consumption and household lifestyle in Japan. One type of report was for households with a night-oriented lifestyle, which were classified by means of frequency analysis; it was evident that such households should shift to a healthy, environmentally friendly, morning-oriented lifestyle. Another type of report was based on cluster analysis: it pinpointed the dates and times when the household consumed much more electricity than with its regular routine. Through panel data regression analysis, it was found that the reports contributed to reducing daily household electricity consumption—as long as a boomerang effect could be avoided. It was also found that the feedback effect was enhanced by activation of consciousness, norms, and motives. It was observed that activation required a good understanding of the characteristics of electricity consumption and lifestyles of each household.

Keywords: residential electricity consumption; energy feedback; lifestyle; frequency analysis; cluster analysis

1. Introduction

Recently, smart electricity metering has received global attention as a means of reducing power consumption in residential areas. The number of smart electric meters installed worldwide will reach 800 million by 2020 [1]. The spread of smart meters in Japan has been slower than in other OECD countries; however, it has been accelerated by the full liberalization of the electricity retail market in April 2016. According to the fourth edition of the Strategic Energy Plan of Japan [2], which was the first plan following the catastrophic 2011 Tohoku earthquake and tsunami, smart meters will be installed in all Japanese households by the early 2020s. Smart meters are a critical technology in establishing “smart communities”, which contribute to an energy-efficient society by integrating information and communication technology (ICT) and various energy technologies [3].

Feedback about electricity consumption is a promising utilization of electricity-use data from smart meters to enhance end-users’ responsiveness, thereby reducing their electricity consumption [4]. Among practical studies of electricity feedback, various types of feedback to households have been provided over recent decades [5]. Most feedback offers information on the recipients' real-time or previous electricity consumption and conservation activities; however, the effect on electricity conservation differs according to the approach adopted [6]. Recent studies based on psychological methods [6,7] have revealed the importance of personalized information to increase household engagement and reduce household energy consumption. Although some empirical studies and feedback reports were conducted by power companies and public institutes [8–10], those studies have not focused on household lifestyle, an important aspect for feedback personalization.

This paper presents the findings from a pilot program of feedback about a household's electricity consumption and its own particular lifestyle. Here, "lifestyle" has a broad meaning: it relates not only to the occupants' specific behaviors, e.g., sleeping, eating, and bathing, but also to their use of home appliances related to such behaviors. To provide personalized feedback, analytic methods were used to identify a household's lifestyle from its electricity-use data, from which tailor-made advice to conserve electricity was proposed according to each household's lifestyle. Reports were sent to 78 households and the feedback effect for reducing household electricity consumption was evaluated by comparing the consumption of recipients and non-recipients. Furthermore, impressions of the report content were assessed by means of a questionnaire.

In Section 2 of this paper, an overview of the technological and theoretical background related to feedback is provided. The analysis methodology for residential electricity-use data is also introduced. In Section 3, the detailed methods adopted with this pilot program are explained. For an accurate evaluation of the feedback effect, a statistically robust method using regression analysis for panel data with cluster-robust standard errors is employed. In Section 4, the results of the pilot program are presented. In Section 5, the feedback effect using reports on conserving electricity is discussed. In Section 6, conclusions about the pilot program are offered and some political implications are outlined.

2. Overview of Related Literature

2.1. Technological Background of Feedback

Feedback has been developed since the 1970s as a behavioral approach to improving end-use energy efficiency; such feedback is provided mainly through energy bills or reports [11–19]. After the 1973–1974 oil crisis, Seaver and Patterson [11] conducted a feedback experiment regarding residential fuel oil conservation. They gave consumers a feedback report about their fuel oil consumption rate (gallons per degree day) that winter and their consumption rate the previous winter. The authors found that the fuel oil consumption of the feedback group was 2.1% lower than that of the control group. Hayes and Cone [12] provided energy information and daily feedback information about electricity consumption to four units in a U.S. university student housing complex. The results showed that feedback produced an 18% reduction in average electricity consumption. By contrast, general information decreased electricity consumption by 30% initially; however, that effect declined to 9% after two weeks. These results imply that personalization is essential to residential electricity management.

Various devices have been developed for the purpose of reinforcing environmentally relevant behavior [13,20–23]. In one of the earliest studies of feedback demonstration, Seligman et al. [13] installed a blue light, which informed occupants that outdoor temperatures were sufficiently low for the air conditioner to be switched off in their kitchens. Ueno et al. [20] developed an advanced metering infrastructure (AMI) called the online Energy Consumption Information System (ECOIS) and installed ECOIS in nine households in Japan. By means of a B5-size laptop computer display, ECOIS provided the households with the 30-min and daily power consumption of every appliance, and it proposed energy-saving actions, e.g., turning off the TV when no one was watching it. By comparing electricity consumption before and after installing ECOIS, the authors found that households in which ECOIS was installed could reduce their electricity consumption by 9%. Wood and Newborough [21] developed another type of AMI, called energy-consumption indicators (ECIs), for the purpose of providing feedback about electricity consumption when cooking. The authors installed ECIs in 31 U.K. households. By comparing electricity consumption between the treatment and control groups before and after ECI installation, the authors found that 14 of the 31 households reduced electricity consumption for cooking by more than 10%; six households had savings of over 20%. These studies imply that more detailed feedback is effective in reducing household electricity consumption.

Following advances in smart metering technologies, large-scale demonstrations using direct feedback have increased since the 1990s [24–30]. Direct feedback constitutes real-time information about electricity consumption [24–26] or electricity consumption plus price [27–30]; it is mainly provided using an in-home display (IHD) [31]. However, reviews of feedback demonstrations have suggested that real-time information is not the only requirement for effective feedback. Faruqui et al. [32] reviewed 12 IHD pilot programs from 1989 to 2010 in four countries (United States, Canada, Australia, and Japan); the authors determined that households could reduce their electricity consumption by 7% on average, within a range of 2.7–18.0%. Through a review of qualitative and quantitative studies on direct feedback via IHDs, Buchanan et al. [33] found limited evidence of the efficacy of direct feedback; the authors maintained that consideration should be given to household engagement.

In order to measure and verify the effect of feedback reports, a few collaborative projects have been also carried out by utility companies and public institutions. For example, Pacific Gas and Electric Company, an electric utility in the United States, sent home energy reports to the residential customers and assessed the impact of behavioral demand response on peak electricity usage on four designated "Summer Saving Days" [8]. In Japan, Jyukankyo Research Institute conducted a home energy report pilot study on 41,200 Hokuriku Electric Power Company's customers [9]. The advice in home energy reports in the USA and Japan was made on the basis of monthly electricity consumption. The Energy Demand Research Project (EDRP) in the United Kingdom was carried out to test consumers' responses to different forms of information about their energy use. About 61,300 customers of four British power companies (EDF, E.ON, Scottish Power, and SSE) participated in the EDRP, and the impact of energy efficiency advice (not personalized to the customer) on annual energy reduction was measured [10].

2.2. Theoretical Background of Feedback

Better understanding of the theoretical background to the causal relationship between energy consumption and feedback is important for increasing household engagement. Using a psychological model to explain the relationship between environmentally relevant behavior and information, Fischer [6] explained how and why feedback on electricity consumption contributes to conserving electricity. Two processes change individual habits into environmentally friendly behavior. Termed norm activation, the first process requires an individual to raise three types of consciousness: (1-1) consciousness of issues; (1-2) consciousness of the relevance of the individual's behavior to the issues; and (1-3) consciousness of the individual's possibilities of changing their behavior. When norm activation is accomplished, an individual is able to undertake norm evaluation and decision making. In the second process, different behaviors are evaluated based on the following: (2-1) personal norms; (2-2) social norms; and (2-3) other motives. Individuals make this evaluation to choose the behavior that maximizes the sum of the norm values.

Schultz et al. [7] suggested that normative information can exert a different effect on environmentally relevant behavior depending on whether the feedback report indicates whether the recipient's behavior is above or below the norm. The authors found that feedback showing that the recipient's energy consumption was below average led to increased energy consumption from baseline. In social psychology related to household electricity consumption, this unintended consequence is termed the "boomerang effect". Schultz et al. also found that the undesirable boomerang effect could be avoided by additional messages of approval or disapproval related to electricity consumption. The authors used a happy face emoticon in reports to recipients whose electricity consumption was below average. Opower [34] has applied these psychological findings to its tailor-made home energy report service in the United States. Toward activating (2-2) "social norms", that report compared a household's electricity consumption with the average consumption in its neighborhood. A pilot program using Opower's feedback service found an average electricity-saving effect of 2.1% [35,36].

2.3. Analysis Methodology of Residential Electricity-Use Data

Advanced analysis of residential electricity-use data is essential for personalization of feedback. Various analysis methodologies have been developed: they have used the regression model [37–40]; time-series analysis [41–49]; and clustering techniques [46–54]. However, most analyses have been aimed at short- and medium-term demand forecasting; relatively few analyses have been directed at tailor-made feedback. Beckel et al. [53] adopted supervised machine learning techniques to estimate specific characteristics of a household, e.g., its socioeconomic status, dwelling, or appliance stock, from its electricity-use data collected from 4232 households in Ireland. Abreu et al. [48] focused mainly on the variation in load profiles in the course of a year. The authors gathered load profiles of up to 14 months for 15 households in Portugal and performed a cluster analysis of those profiles to identify each household's routines over a year. Their analysis identified persistent daily routines and patterns of consumption or baselines typical for specific weather or daily conditions, e.g., hot working days and cold weekend days. From a power network manager point of view, Espinoza et al. [49] developed a methodology aiming for both short-term forecasting and customer profile identification. They identified eight clusters from 245 pieces of hourly load data from a HV-LV substation within the Belgian grid, using a periodic autoregression model and a clustering technique. Jardini et al. [40] defined the representative daily load profiles by monthly electricity consumption ranges and by consumers type, from load curves of residential, commercial and industrial consumers of the Utilities of Electric Energy of São Paulo State, Brazil. They also presented a methodology for the aggregation of different customers' load profiles.

Ozawa et al. [47] developed two kinds of electricity data analysis methods to investigate relatively detailed variations in load profiles for a specific period of the year (for one week or one month); the purpose was to demonstrate the relationship between household electricity consumption and lifestyle. With the first method, the authors performed a frequency analysis of the weekly load profiles of individual households; they classified 1072 households according to the highest peak in the spectrum distribution. The households were divided into groups based on the representative frequencies, which were calculated for each household. Figure 1 shows an example of the frequency analysis. The authors found that the representative frequencies for over 75% of the households were a 12-h or 24-h period. Ozawa et al. found that the households in the 12-h group had a morning-oriented lifestyle and consumed on average 5.3% less electricity than households in the 24-h period group, which had a night-oriented lifestyle. A morning-oriented lifestyle also has health benefits [55–57], which can be viewed as a (2-3) motive for changing behavior. With the second method, Ozawa et al. performed a cluster analysis of each household's daily load profiles to determine the typical load pattern. From the cluster analyses, various load patterns and the corresponding dates for each load pattern were obtained. For each household, the load pattern when the household followed a regular routine for the month was defined based on the most common pattern for that month. Figure 2 shows an example of the cluster analysis. Based on an index evaluating the validity of clustering, Ozawa et al. noted that the best cluster analysis could be performed for each household when using the complete linkage method and with five clusters. They also found that most of the 1072 households consumed less electricity when they followed a regular routine. Households can activate their own (2-1) "personal norms" by reflecting on their daily life and electricity consumption. Figure 3 summarizes the assumed causal connections between norms or motives and feedback obtained through an analysis and comparison of household electricity consumption.

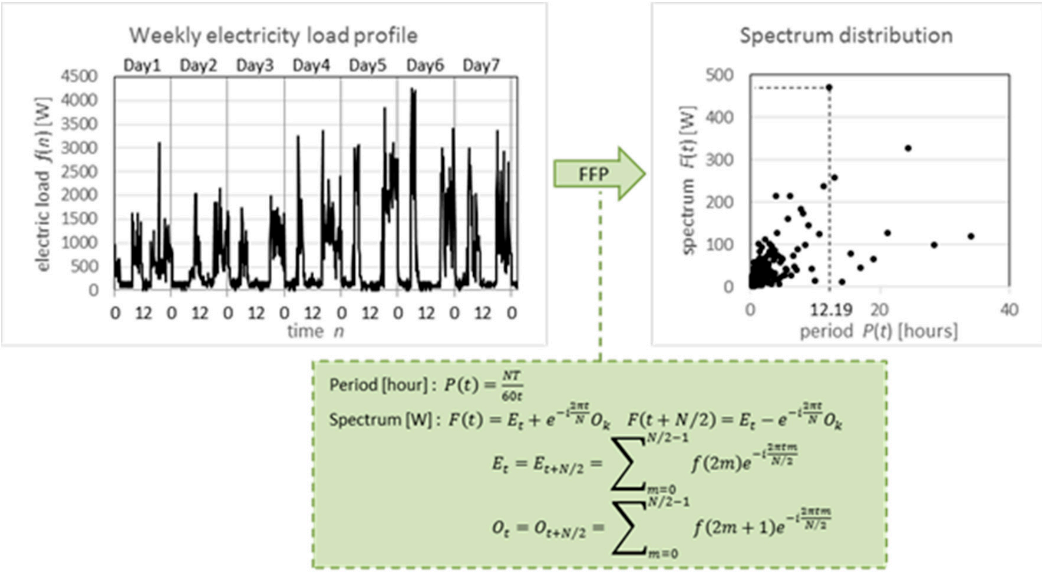


Figure 1. Example of frequency analysis [47].

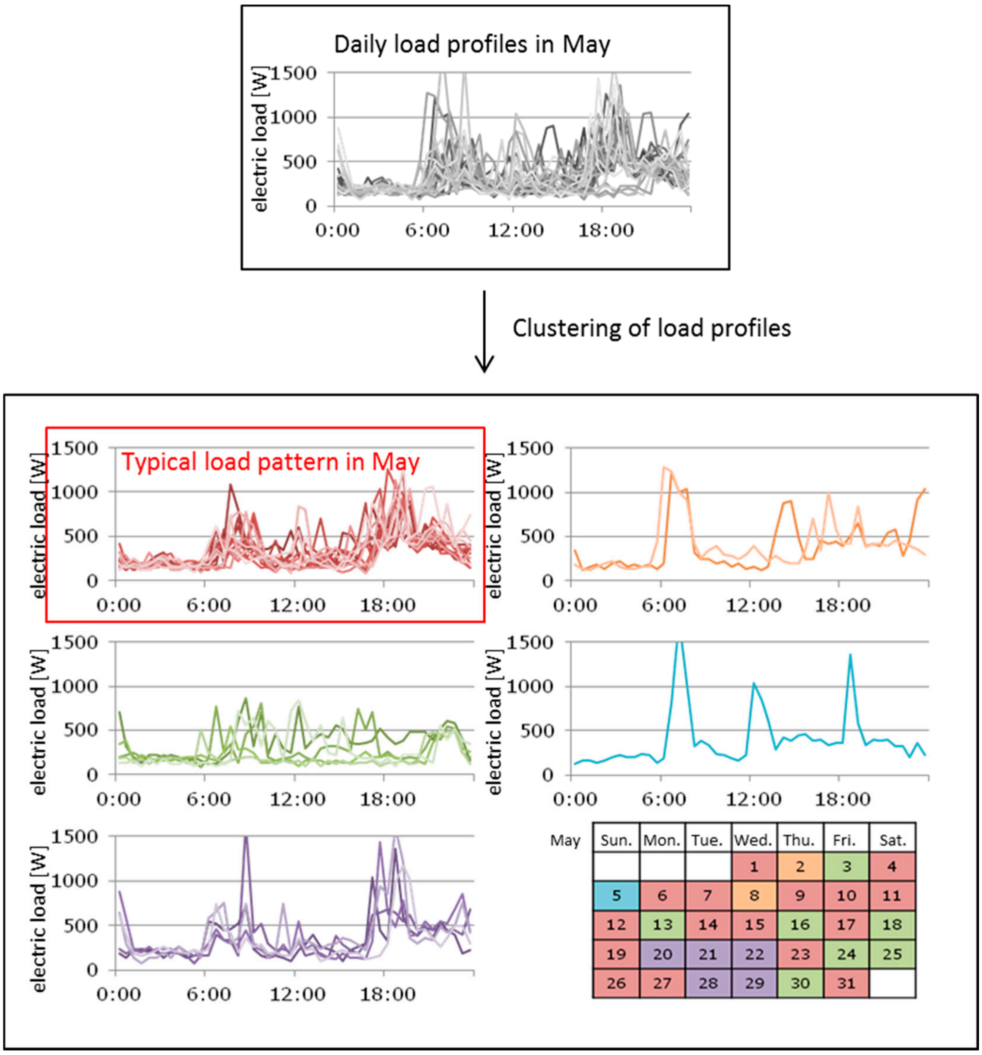


Figure 2. Example of cluster analysis [47].

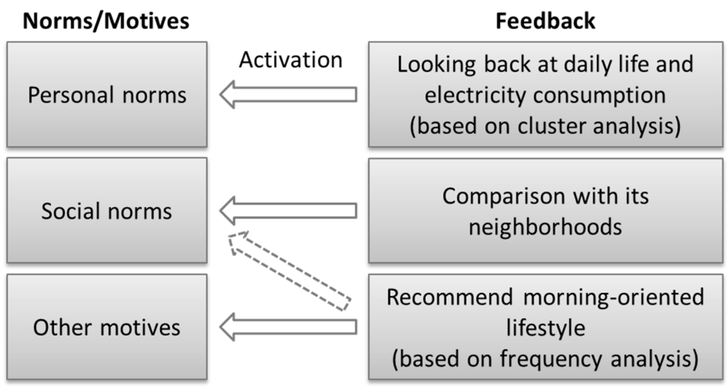


Figure 3. Assumed causal connections between norms or motives and feedback.

3. Materials and Methods

3.1. Participant Recruitment

Participants for the pilot program were recruited among residents living in detached houses with a home energy management system (HEMS). With the IHD of the HEMS, residents can monitor their real-time electricity consumption and check their electricity consumption records over the previous year. Using the HEMS, residents are also able to switch the house's lights and air conditioners on and off. The houses in the pilot program had similar building characteristics, having been constructed after 2011 by the same company using the latest heat-insulation criteria. Letters were sent to 300 households, inviting their participation in the feedback pilot program; positive participation responses were received from 78 households. Most of the participants lived in the Kanto, Chubu, or Kansai regions, which have similar climate conditions. Opt-in pilot programs such as this tend to show a better feedback effect on reducing household electricity consumption than opt-out programs [31]. An opt-in method was chosen because such methods are highly recommended by research ethics committees.

3.2. Electricity Feedback Reports and Questionnaire

Feedback reports were furnished by gathering data about the 78 households' electricity use for each 30-min period (kWh/30 min) from 1 May to 30 August 2015. A 30-min time interval is the basic specification required for smart meters in Japan [58]. Electricity demand data measured during each 30-min period have been also used in the feedback demonstrations in Japan [20,30]. A feedback report and a questionnaire were sent to 78 households on 28 September 2015. The methods of Ozawa et al. [47] were applied to derive the report content for each household from the 30-min electricity demand data of the household. First, a frequency analysis of the household's weekly load profile was performed. If the spectrum distribution of the weekly load profile showed its greatest peak with a 24-h period, it is determined that the household had a night-oriented weekly lifestyle. Conversely, if the distribution displayed its highest peak with a 12-h period, it is determined that the household had a morning-oriented lifestyle. A type A report was sent to households that satisfied the following conditions: (1) the household spent a night-oriented lifestyle for over seven weeks in the 13 weeks from June to August; (2) the household spent a night-oriented lifestyle for more than one week in the four weeks in August; (3) the household consumed more electricity than the average household in August. Second, for each household except those in the type A group, a cluster analysis of the daily load profiles in August was performed to classify them into one of five patterns, and the typical load pattern of the household was identified. If the daily average electricity consumption of the typical load pattern was less than the average consumption with the other patterns, a type B report was sent. Finally, a type C report was sent to the remaining households. Figure 4 is a flow chart showing how the three types of reports were sent to each household.

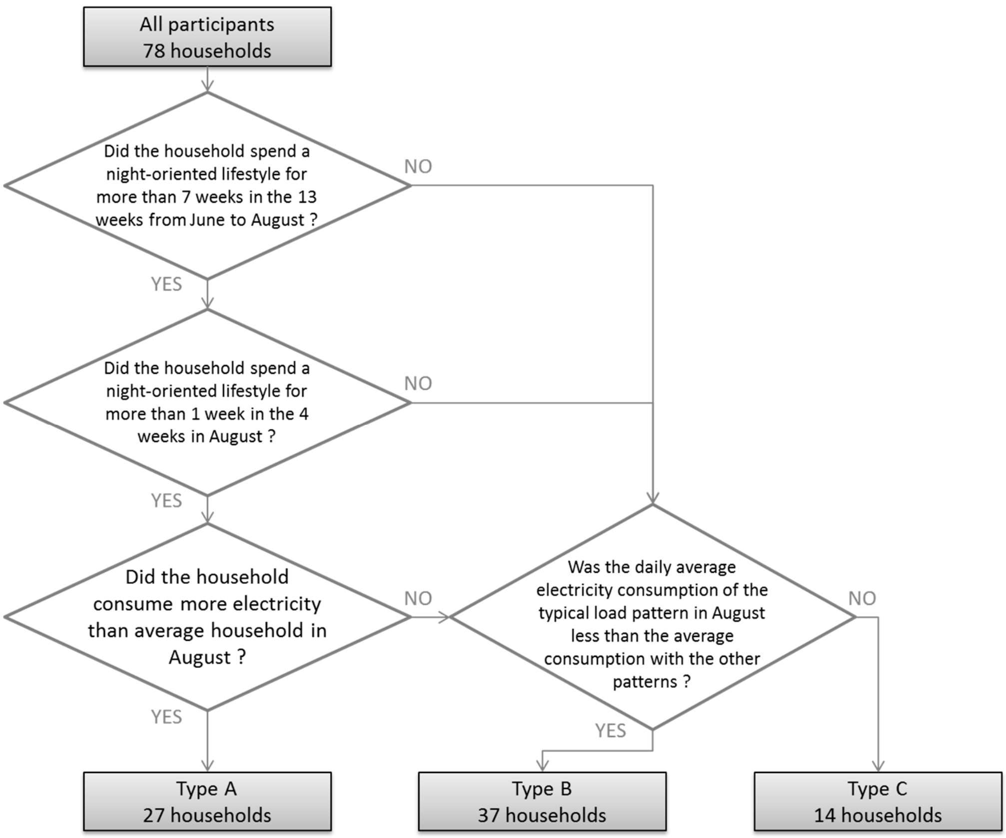


Figure 4. Flow chart of household classification and report type.

With the questionnaire enclosed with the feedback report, recipients were asked about their characteristics with respect to personal attributes and home energy use. It should be noted that five of the 78 households that received a feedback report failed to respond. Figure 5a shows the composition of the recipient families. The average numbers of family members were as follows: all, 3.70; type A, 3.68; type B, 3.66; and type C, 3.80. Figure 5b displays the recipient's family type composition: 74% of the recipients were couples with children. The composition by report type was similar among the recipient families.

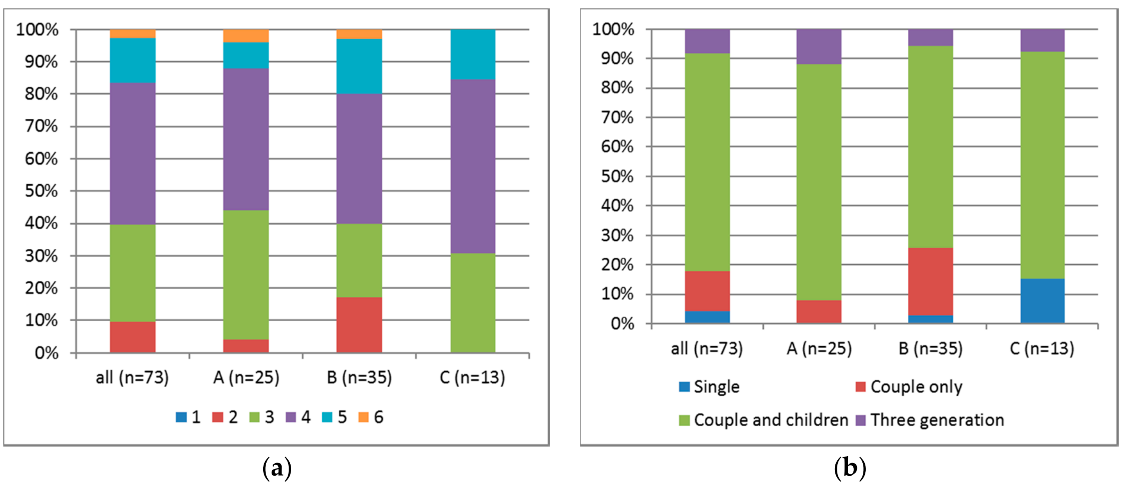
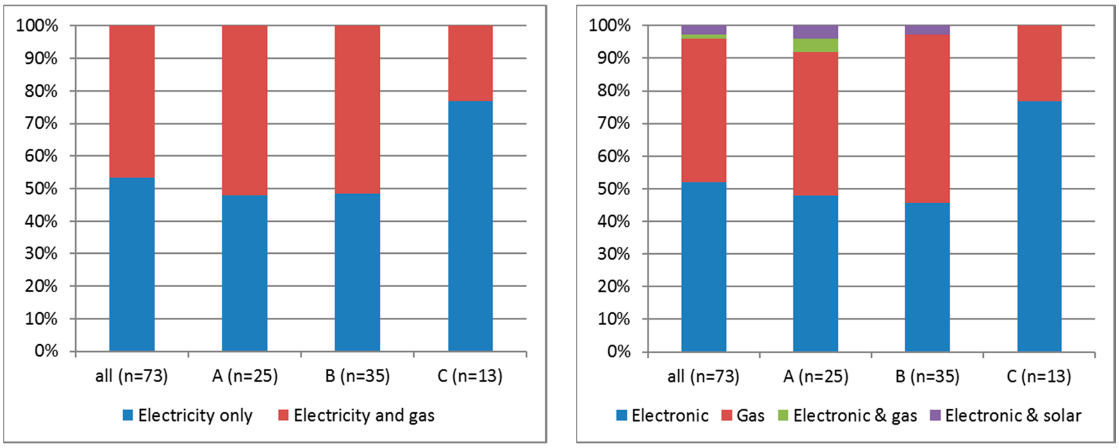


Figure 5. Recipient personal attributes: (**a**) number of people in the recipient's family; (**b**) recipient family type.

Figure 6a shows the type of energy utility; Figure 6b presents the type of water heaters used in the recipient homes. About half of the recipients' homes were all-electric and used electric heaters; the other half used both electricity and gas, employing gas heaters. In a comparison of households by report type, type C households tended to be all-electric.



(**a**) (**b**)

Figure 6. Recipients' home energy use: (**a**) energy utility in recipients' homes; (**b**) type of water heater in recipients' homes

3.3. Feedback Report Content

Figures 7–9 present samples of the feedback reports. The feedback report was divided into three areas: "Comparison with other households", "Daily electricity usage", and "Energy-saving advice for you".

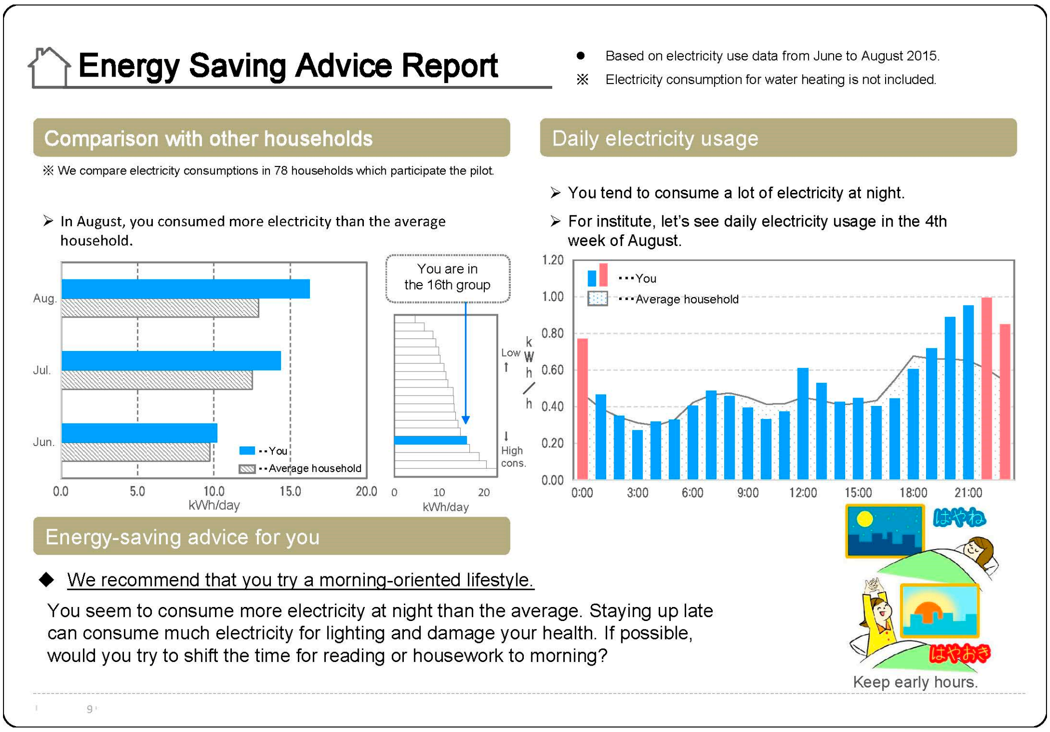


Figure 7. Sample of type A feedback report.

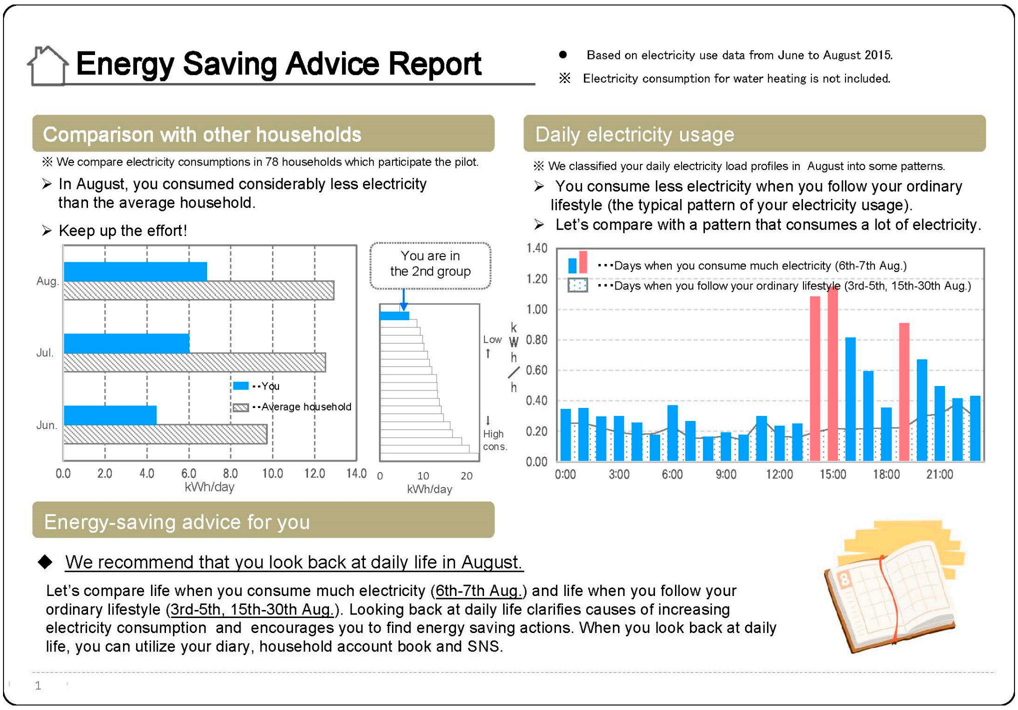


Figure 8. Sample of type B feedback report.

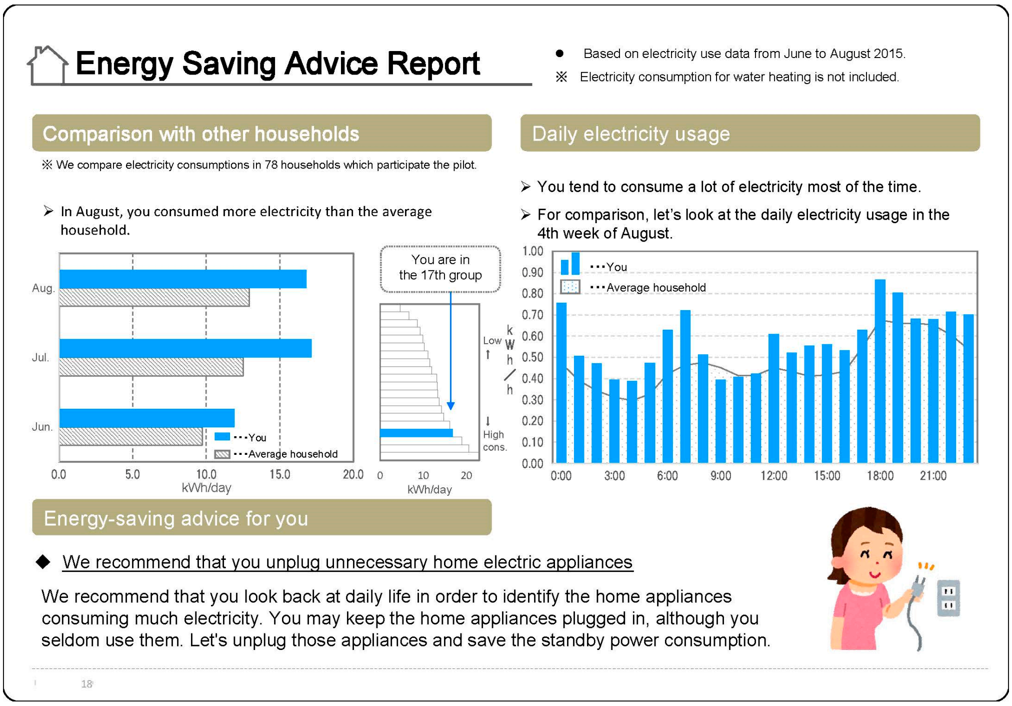


Figure 9. Sample of type C feedback report.

3.3.1. Comparison with Other Households

This section, which is common to type A, B, and C reports, is designed to activate (2-2) recipients' "social norms". It provides information about the basic features of a recipient's electricity consumption by comparing their daily consumption with the average of other recipients. The result is summarized in a couple of sentences under the title. The figure on the left compares daily electricity consumption in June, July, and August: the blue bars indicate the recipient's daily electricity consumption; the gray bars show the average consumption of all participants. The graph on the right indicates all participants classified into 20 groups in the order of daily electricity consumption in August. The blue column indicates consumption in the groups to which the recipient belongs.

3.3.2. Daily Electricity Usage

This section enables recipients to understand the detailed characteristics of their electricity usage. It does so by comparing the recipient's electricity profile in a particular week or on a particular day with their electricity profile on another day or with another household's electricity profile for the same period. The contents of type A, B, and C reports differ from one another.

In a type A report (for households with a night-oriented lifestyle), this section compares the recipient's average load profile in a week of August (blue bars) with the average load profile of all participants in the same week (black curve). In this way, it indicates that the household tends to consume considerably more electricity at night than the average household (times with a conspicuous gap are shown by pink bars).

In a type B report (for households that consume less electricity when they follow their ordinary lifestyle), this section compares two of the five load patterns obtained by cluster analysis of each household's daily load profiles in August. One pattern is the typical load pattern: the load pattern that appears most frequently in that month (black curve). Another is the consuming load pattern: the load pattern in which daily average electricity consumption is greatest among the five patterns (blue bars). This comparison pinpoints the dates and times when the household consumes substantial amounts of electricity (highlighted with pink bars).

A type C report is similar to a type A report: the recipient did not consume much electricity at night.

3.3.3. Energy-Saving Advice for You

This content corresponds to daily electricity usage and differs among the report types. The advice in type A and B reports can activate the recipient's norms and motives. In the type A report, it is recommended that the recipient adopts an energy-saving morning-oriented lifestyle, which consumes less electricity for air conditioning and lighting at night. It is also suggested that a morning-oriented lifestyle is healthy toward activating (2-3) "other motives". In the type B report, it is recommended that the recipient should reflect on their daily life. A reconsideration of aspects of daily life contributes to activating (2-1) "personal norms": personal ideas about how one should act. In the type C report, general tips for reducing household electricity consumption are offered, e.g., unplugging unnecessary electrical appliances.

3.4. Evaluation of Feedback Report on Reducing Household Electricity Consumption

To evaluate how much household electricity consumption was reduced (or perhaps increased) after reading the energy feedback report, daily electricity consumption before and after feedback need to be analyzed. John Stuart Mill proposed a set of conditions that have to be met in order to demonstrate the relationship between cause and effect: (1) the supposed cause has to precede the supposed effect in time; (2) the supposed cause must correlate with the supposed effect; and (3) other than the cause, any other plausible explanations cannot be identified for the effect [31]. To confirm the causal relationship between electricity consumption and feedback, regression analysis was performed for panel data of daily electricity consumption among the 87 households that received the feedback and the other households, which did not receive it. In the social sciences, difference in difference approaches based on panel data regressions are commonly used to calculate the effect of treatment [31].

In Section 3.4.1, the regression analysis for the panel data is presented. There are two types of regression analysis models for panel data: the fixed effects and random effects models. Both models were constructed and the validity of each was assessed using a statistical test. In Section 3.4.2, using panel data regression analysis, the evaluating method of the feedback effect on household electricity consumption is shown. To determine the feedback effect from among many other factors, other feasible explanations, such as outside weather conditions, were taken into account.

3.4.1. Regression Analysis for Panel Data

Regression analysis for panel data is an analytic method used mainly in the field of econometrics [59,60]. Suppose there are the properties of I individuals and T time periods for each individual. For the panel data, the multiple regression model with K independent variables can be written as Equation (1):

$$Y_{it} = \alpha_i + \beta_1 X_{it}^1 + \beta_2 X_{it}^2 + \cdots + \beta_k X_{it}^k + \cdots + \beta_K X_{it}^K + \varepsilon_{it} = \alpha_i + \boldsymbol{b}\boldsymbol{x}_{it} + \varepsilon_{it}, \quad (1)$$

where Y_{it} is the explained variable of individual i $(i = 1, 2, \cdots, I)$ in time period t $(t = 1, 2, \cdots, T)$; X_{it}^k is the kth $(k = 1, 2, \cdots, K)$ independent variable of individual i in time period t; $\boldsymbol{x}_{it} = {}^t\left(X_{it}^1, X_{it}^2, \cdots, X_{it}^k, \cdots, X_{it}^K\right)$ is the vector notation of the independent variables; α_i is the intercept, which is also termed the individual effect in the field of panel data analysis; β_k is the parameter of kth independent variables; $\boldsymbol{b} = (\beta_1, \beta_2, \cdots, \beta_k, \cdots, \beta_K)$ is the vector notation of the parameters; and ε_{it} is the error term, $\varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right)$.

With the fixed effects model, the individual effect α_i is calculated for each individual. Therefore, if the number of time periods T is small, estimates cannot be obtained owing to the limited degree of freedom. The random effects model avoids this difficulty by presenting individual effect α_i as a combination of the constant term α and error term ν_i. This satisfies the relation in Equation (2); however, this model requires that individual effect α_i and independent variable X_{it}^k are uncorrelated:

$$\begin{aligned} &E[\nu_i] = 0 \\ &Cov(\nu_i, \nu_j) = E[\nu_i \nu_j] = \begin{cases} \sigma_\nu^2 & (i = j) \\ 0 & (i \neq j) \end{cases} . \\ &Cov(\varepsilon_{it}, \nu_j) = E[\varepsilon_{it} \nu_j] = 0 \end{aligned} \quad (2)$$

The consistency of models (fixed effects vs. random effects) can be evaluated using the Hausman test [61]. The test statistic H follows the chi-square distribution with K degrees of freedom, as shown in Equation (3):

$$H = {}^t\left(\hat{\boldsymbol{b}}_{fe} - \hat{\boldsymbol{b}}_{re}\right)\left[\hat{V}\left(\hat{\boldsymbol{b}}_{fe}\right) - \hat{V}\left(\hat{\boldsymbol{b}}_{re}\right)\right]^{-1}\left(\hat{\boldsymbol{b}}_{fe} - \hat{\boldsymbol{b}}_{re}\right) \sim \chi_K^2, \quad (3)$$

where $\hat{V}\left(\hat{\boldsymbol{b}}_{fe}\right)$ and $\hat{V}\left(\hat{\boldsymbol{b}}_{re}\right)$ are estimates of the covariance matrix of the estimated parameters with the fixed and random effects models. If H is small, both the fixed and random effects models are valid. If H is sufficiently large, only the fixed effects model is valid.

3.4.2. Evaluating Feedback Effect on Household Electricity Consumption Using Panel Data Regression Analysis

The panel data regression analysis model is used to evaluate the effect of feedback. The explained variable in the regression analysis model was daily electricity consumption of household i on day t $Eday_{it}$ (kWh/day). Electricity-use data from 1 May to 1 November 2015 was gathered; thus, the number of time periods $T = 185$; $t = 1$ corresponded to May 1 and $t = 185$ corresponded to 1 November. Electricity-use data for 78 households that received a feedback report (treatment group) and 568 households that did not receive it (control group) was obtained; in this way, panel data of the households' daily electricity consumption was created. Both the treatment and control groups lived in houses with similar building characteristics and HEMSs. In the questionnaire enclosed with the feedback report, recipients were asked about the date when they read the report so as to set the period after treatment for each recipient. The period before the day a household read the feedback is defined as "before treatment" and the period on and after that day is defined as "after treatment".

Three evaluation methods were undertaken: lumped evaluation, which assessed the effect of all types of reports together; evaluation by report type, which determined the effect of each type of report; and evaluation by household, which assessed the effect of each type of report on each household. With lumped evaluation, regression analysis was performed for the panel data of all 645 households. With evaluation by report type and evaluation by household, the 568 households that did not receive a feedback report were classified into three groups according to the flow chart in Figure 4; panel data was made for each group. Table 1 displays the number of households with panel data for each evaluation. It should be noted that owing to missing data, 10 of the 78 households that received feedback were excluded from the evaluation.

Table 1. Number of households in lumped evaluation, evaluation by report type, and evaluation by household.

	Lumped Evaluation	Evaluation by Report Type / Evaluation by Household		
		Type A	**Type B**	**Type C**
# households	636	178	343	115
# household which received a feedback report	68	24	32	12
# household which did not receive a feedback report	568	154	311	103

A linear regression model was constructed to assess the daily electricity consumption of household i on day t $Eday_{it}$ (kWh/day). Explanatory variables for the daily electricity consumption are set based on the linear regression model developed by Mukai et al. [30]. In order to evaluate the feedback effect on peak electricity demand in summer, they chose the following six parameters as the explanatory variables of the linear regression model: the average temperature of the peak times, the average humidity of the peak times, the average temperature of the previous three days, a weekday dummy, an indicator specifying the post-treatment period, and an indicator specifying the post-treatment period by feedback type. In this study, seven explanatory variables were considered: three about climate conditions (X_{it}^{cool}, X_{it}^{heat}, X_{it}^{humid}); one about weekdays or holidays (X_t^{holi}); one about change over time (X_{it}^{time}); and two about feedback reports (X_{it}^{read}, $X_{it}^{below\_average}$).

X_{it}^{cool} and X_{it}^{heat} are variables representing the effect of outdoor temperature. X_{it}^{cool} (degree C) represents space cooling demand and is given by Equation (4); X_{it}^{heat} (degree C) represents space heating demand and is given by Equation (5). Here, $TEMPoa_{it}$ (degree C) is the daily average outside air temperature on day t at the prefectural capital where household i was resident. These variables were based on "heating and cooling degree day": these were indices to estimate annual energy consumption for space heating and cooling. The heating and cooling degrees were calculated on a daily basis to capture daily electricity consumption for space cooling and heating in each household. A number of variables with different threshold values were considered and the most appropriate one was selected. Both heating and cooling degrees are considered, because the assessment period of this pilot program is from 1 May to 1 November. The average temperature of the previous three days is excluded from explanatory variables, because it has a correlation with X_{it}^{cool} and X_{it}^{heat}, which make difficult to obtain accurate evaluation results due to the multicollinearity between a pair of explanatory variables.

$$X_{it}^{cool} = \begin{cases} TEMPoa_{it} - 24 & (TEMPoa_{it} \geq 24) \\ 0 & (TEMPoa_{it} < 24) \end{cases} \tag{4}$$

$$X_{it}^{heat} = \begin{cases} 14 - TEMPoa_{it} & (TEMPoa_{it} \leq 14) \\ 0 & (TEMPoa_{it} > 14) \end{cases} \tag{5}$$

X_{it}^{humid} [%] is the daily average humidity on day t at the prefectural capital where household i was resident.

X_t^{holi} is a dummy variable representing whether day t was a weekday ($X_t^{holi} = 0$) or holiday ($X_t^{holi} = 1$). Holidays are Saturdays, Sundays, and national holidays: in 2015, 4–6 May, 20 July, 21–23 September, and 12 October. This variable corresponds to the weekday dummy in the linear regression model developed by Mukai et al. [30].

X_{it}^{time} is a dummy variable representing change in household electricity consumption over time. This dummy variable is set to remove time-dependent influences except climate condition. $X_{it}^{time} = 1$ if day t was after 30 September when households received feedback reports, and $X_{it}^{time} = 0$ if t was before 29 September. This variable corresponds to the indicator specifying the post-treatment period in the linear regression model developed by Mukai et al. [30].

X_{it}^{read} is a dummy variable representing feedback effect on household electricity consumption. Let t_i^{read} be the date when household i read a feedback report. $X_{it}^{read} = 1$ if day t was after the following day of t_i^{read} ($t > t_i^{read}$); $X_{it}^{read} = 0$ if day t was before t_i^{read} ($t \leq t_i^{read}$) or the household i did not receive a feedback report. This variable corresponds to the indicator specifying the post-treatment period by feedback type in the linear regression model developed by Mukai et al. [30].

$X_{it}^{below\_average}$ is a dummy variable representing the boomerang effect of the feedback report on household electricity consumption. If consumption in August was below the average, the report stated, "In August, you consumed (considerably) less electricity than the average household" in the "Comparison with other households" section. Of 68 households, 31 received such a report: eight households received type A; 17 households received type B; and six households received type C. $X_{it}^{below\_average} = 1$ if day t is the next day after t_i^{read} ($t > t_i^{read}$) and the report stated, "In August, you consumed (considerably) less electricity than the average household". Otherwise, $X_{it}^{below\_average} = 0$.

With lumped evaluation and evaluation by report types, two linear regression models composed by the above explanatory variables is assumed. With the six-variable model, Equation (6), the total effect of all content in the report (X_{it}^{read}) on household electricity consumption could be evaluated. With the seven-variable model, Equation (7), the boomerang effect of the message, "In August, you consumed (considerably) less electricity than the average household" ($X_{it}^{below\_average}$) and the feedback effect of the other information (X_{it}^{read}) on household electricity consumption could be separately assessed.

To avoid an inaccurate evaluation result caused by heteroscedasticity and autocorrelation in the models, cluster-robust standard errors were calculated using Thompson's method [62] and that of Cameron et al. [63]:

$$Eday_{it} = \alpha_i + \beta_{cool} X_{it}^{cool} + \beta_{heat} X_{it}^{heat} + \beta_{humid} X_{it}^{humid} + \beta_{holi} X_t^{holi} + \beta_{time} X_{it}^{time} + \beta_{read} X_{it}^{read} + \varepsilon_{it} \quad (6)$$

$$Eday_{it} = \alpha_i + \beta_{cool} X_{it}^{cool} + \beta_{heat} X_{it}^{heat} + \beta_{humid} X_{it}^{humid} + \beta_{holi} X_t^{holi} + \beta_{time} X_{it}^{time} + \beta_{read} X_{it}^{read} + \beta_{eff} X_{it}^{below\_average} + \varepsilon_{it}. \quad (7)$$

For evaluation by household, a linear regression model is given by Equation (8). β_{read_i} is estimated using the feedback effect on household i's electricity consumption:

$$Eday_{it} = \alpha_i + \beta_{cool} X_{it}^{cool} + \beta_{heat} X_{it}^{heat} + \beta_{humid} X_{it}^{humid} + \beta_{holi} X_t^{holi} + \beta_{time} X_{it}^{time} + \beta_{read_i} X_{it}^{read} + \varepsilon_{it}. \quad (8)$$

To determine which household was most influenced by a type B feedback report, a regression analysis between the features of households' electricity consumption and the feedback effect was performed. The regression formula is given in Equation (9), where $Eday_{typ_i}$ (kWh/day) is the daily average electricity consumption of a typical load pattern in August, $Eday_{most_i}$ (kWh/day) is the daily average electricity consumption of a consuming load pattern in August, and $R_i = Eday_{most_i} / Eday_{typ_i}$ is the ratio of electricity consumption of the typical load pattern and consuming load pattern:

$$\hat{\beta}_{readB_i} = \alpha_i + \beta_{Etyp} Eday_{typ_i} + \beta_{Emost} Eday_{most_i} + \beta_R R_i + \varepsilon_i \quad (8)$$

4. Results

4.1. Recipients' Impressions of the Report

With the questionnaire enclosed with the feedback report, recipients were asked for their impressions of the report. From the questionnaire responses, it was found that most households found the report beneficial. Responding to the question as to whether the report was useful, 86% of recipients answered in the affirmative. This result underlines the appropriateness of tailor-made feedback for many households in addition to the monitoring of real-time electricity consumption through the IHD. It should be noted that the participants in this opt-in demonstration pilot program tended to have high interest in the feedback report. The recipients' favorable impression of the feedback would appear to reflect their inclination to follow the advice. Responses to the question as to whether recipients followed energy-saving advice indicated that about 70% of recipients indicated willingness to do so.

4.2. Evaluation of Feedback Report on Reducing Household Electricity Consumption

4.2.1. Daily Average Electricity Consumptions of Treatment and Control Groups

Figure 10 shows the comparison results of the daily average electricity consumption of the treatment and control groups before the feedback (June to August 2015); the electricity consumption of the two groups was similar.

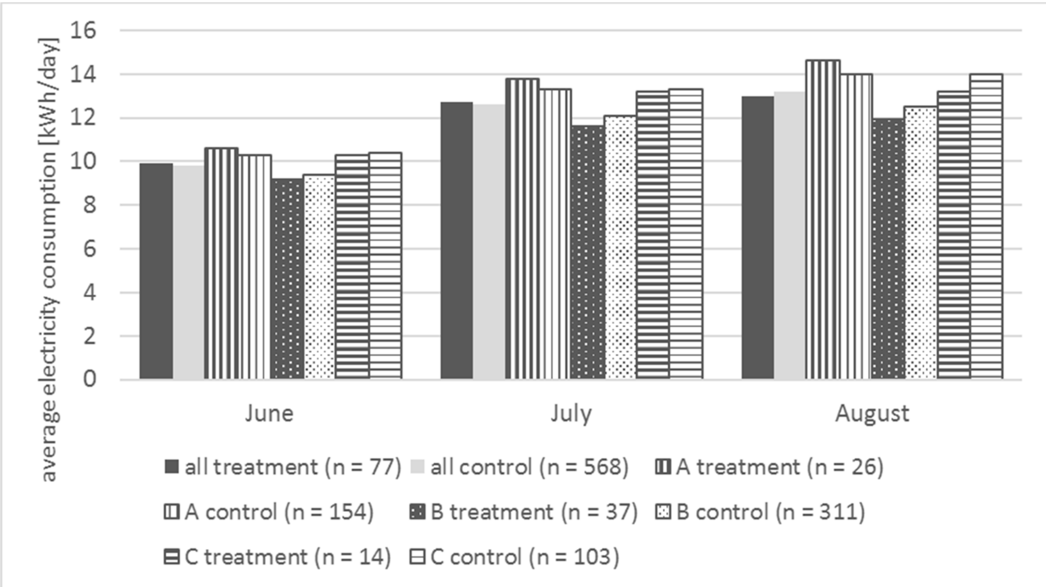


Figure 10. Daily average electricity consumption of the treatment and control groups.

4.2.2. Lumped Evaluation

The electricity-saving effect was evaluated for all the report types using the electricity data of 636 households (68 received a feedback report; 568 did not). Table 2 shows the correlation coefficients of the explanatory variables. The pair of variables with the strongest correlation was X_{it}^{read} and $X_{it}^{below\_average}$ (+0.67): both were dummy variables representing the feedback effect. The other pairs had a weak correlation (−0.30 to +0.30).

Table 2. Correlation coefficients of the explanatory variables.

	X_{it}^{cool}	X_{it}^{heat}	X_{it}^{humid}	X_{t}^{holi}	X_{it}^{time}	X_{it}^{read}	$X_{it}^{below\_average}$
X_{it}^{cool}	1.00						
X_{it}^{heat}	−0.06	1.00					
X_{it}^{humid}	−0.03	–0.06	1.00				
X_{t}^{holi}	−0.01	0.04	−0.06	1.00			
X_{it}^{time}	−0.25	0.20	−0.26	−0.00	1.00		
X_{it}^{read}	−0.07	0.09	−0.08	0.00	0.29	1.00	
$X_{it}^{below\_average}$	−0.05	0.04	−0.05	0.00	0.19	0.67	1.00

Table 3 presents the result of the regression analysis for the fixed effects and random effects models with six explanatory variables (Equation (6)). With both models, the daily electricity consumption of a household increased significantly when the outdoor temperature was high (X_{it}^{cool}) or low (X_{it}^{heat}), when the outdoor humidity was high (X_{it}^{humid}), and on holidays (X_{t}^{holi}). However, daily electricity consumption increased, though not significantly, after the household read the feedback report (X_{it}^{read}). The two models had almost the same values of estimated coefficients. That is because the number of evaluation time periods was sufficiently large to perform regression analysis for the panel data. The result of the Hausman test indicates that both models were valid.

Table 3. Result of regression analysis (six variables, lumped).

	Fixed Effect Model		**Random Effect Model**	
	Coefficients	**Standard Errors**	**Coefficients**	**Standard Errors**
X_{it}^{cool}	0.937 ***	0.028	0.937 ***	0.028
X_{it}^{heat}	0.523 ***	0.066	0.522 ***	0.066
X_{it}^{humid}	0.035 ***	0.003	0.035 ***	0.003
X_{t}^{holi}	0.218 ***	0.077	0.218 ***	0.077
X_{it}^{time}	0.014	0.070	0.014	0.070
X_{it}^{read}	0.067	0.186	0.067	0.186
Adj. R-squared	0.3534		0.3514	
Hausman test	Null hypothesis is true. (Both models are valid.)			

*** $p < 0.01$.

Table 4 shows the result of the regression analysis for the fixed effects and random effects models with seven explanatory variables (Equation (7)). As with the result of the regression analysis model with six explanatory variables, the variables for outdoor temperature (X_{it}^{cool}, X_{it}^{heat}), outdoor humidity (X_{it}^{humid}), and holiday (X_{t}^{holi}) significantly contributed to increased daily household electricity consumption. Regarding the effect of feedback reports, daily electricity consumption increased significantly after a household read the message "In August, you consumed (considerably) less electricity than the average household" from the report ($X_{it}^{below\_average}$). Without this effect, household electricity consumption decreased by −0.382 kWh/day (based on the fixed effects model) after reading the feedback report (X_{it}^{read}); that is equivalent to a 3.22% reduction in daily average consumption for all households from June to August. Both the fixed effects and random effects models showed almost the same results. The result of the Hausman test indicated that the result of the fixed effects model should be applied.

Table 4. Result of regression analysis (seven variables, lumped).

	Fixed Effects Model		Random Effects Model	
	Coefficients	**Standard Errors**	**Coefficients**	**Standard Errors**
X_{it}^{cool}	0.937 ***	0.028	0.937 ***	0.028
X_{it}^{heat}	0.526 ***	0.066	0.525 ***	0.066
X_{it}^{humid}	0.035 ***	0.003	0.035 ***	0.003
X_{t}^{holi}	0.218 ***	0.077	0.218 ***	0.077
X_{it}^{time}	0.014	0.070	0.014	0.070
X_{it}^{read}	–0.382	0.281	–0.375	0.281
$X_{it}^{below\_average}$	0.986 ***	0.341	0.972 ***	0.343
Adj. R-squared	0.3538		0.3544	
Hausman test	Null hypothesis is false. (Only fixed effect model is valid)			

*** $p < 0.01$.

4.2.3. Evaluation by Report Type

The electricity-saving effect was determined according to each report type. With the lumped evaluation, there was little difference between the estimated coefficients of the fixed effects and those of the random effects model; that was because the evaluation period was sufficiently long ($T = 185$). In addition, in the case of the lumped evaluation using the seven-variable model, the Hausman test indicated that only the fixed effects model was valid. Accordingly, the results for that model are presented.

Figures 11 and 12 show the coefficients of X_{it}^{read} and $X_{it}^{below\_average}$ estimated for each report type (full sets of the regression analysis results appear in Appendix A Tables A1–A3). With each report type, the estimated coefficient of $X_{it}^{below\_average}$ was positive: type A, 1.407 kWh/day; type B, 0.504 kWh/day; and type C, 1.062 kWh/day. With regard to feedback effect, the coefficients of X_{it}^{read} estimated from the seven-variable model were all negative. The greatest impact was shown by type A. The difference in household electricity consumption before and after the feedback with type A was −0.726 kWh/day: a 5.76% reduction in daily average consumption of type A households from June to August, when the report did not state "In August, you consumed (considerably) less electricity than the average household". The feedback effects of types B and C without the boomerang effect were, respectively, −0.084 kWh/day and −0.046 kWh/day. When comparing the reduction rates per daily average consumption, the feedback effect of type B (−0.74%) was twice that of type C (−0.37%). The coefficient of X_{it}^{read} with type A estimated from the six-variable model was also negative. Household electricity consumption decreased after the household read a type A report.

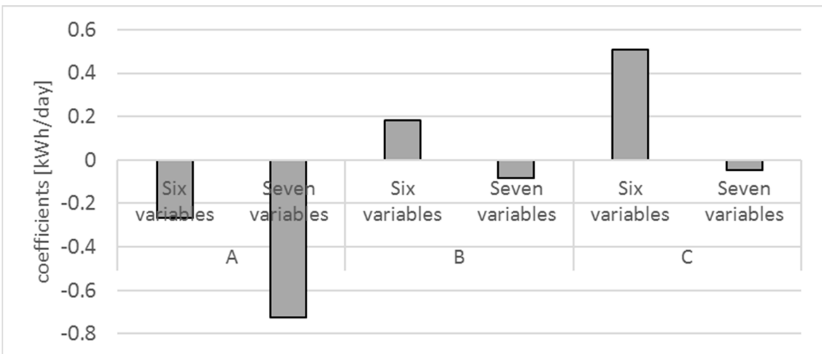


Figure 11. Coefficients of X_{it}^{read} (fixed effects model).

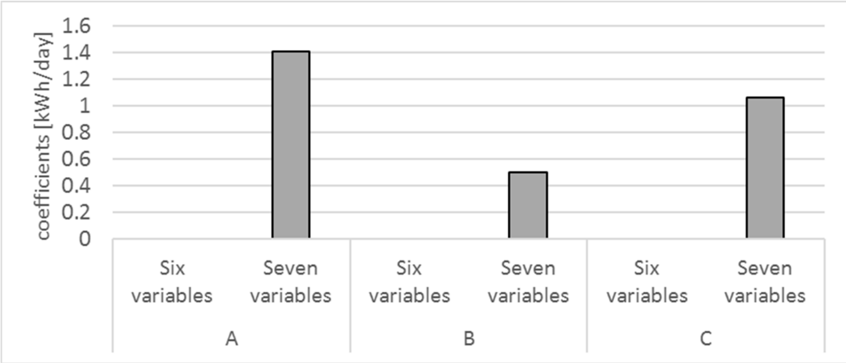


Figure 12. Coefficients of $X_{it}^{below\_average}$ (fixed effects model).

4.2.4. Evaluation by Household

The result of the electricity-saving effect was determined for each household that received a type B report. Table 5 shows the regression analysis result of the feedback effect on each household for that report. The estimated coefficients of $Eday_{typ_i}$ and R_i were significantly negative. This result suggests that a household decreased its electricity consumption upon receiving a type B report if its daily average electricity consumption with the typical load pattern before the feedback was high and the consumption of the consuming load pattern was much higher than that of the typical load pattern.

Table 5. Regression analysis result (type B).

	Coefficients	**Standard Errors**
α_i	5.932 **	2.460
$Eday_{typ_i}$	−0.530 **	0.253
$Eday_{most_i}$	0.229	0.143
R_i	−2.468 *	1.306
Adj. R-squared	0.1611	
F stats.	2.9844 **	

* $p < 0.10$; ** $p < 0.05$.

5. Discussion

The pilot program produced findings about the effect of feedback on a household's electricity consumption and its lifestyle. The results indicate that the activation of consciousness, norms, and motives based on information about household lifestyle has an influence on the feedback effect. In particular, the results emphasized the importance of (2-3) "other motives". The evaluation result by report type suggests that a type A report has a greater effect on household electricity consumption than the other types. A type A report was sent to households that tended to spend a night-oriented lifestyle. From a comparison of the household's average load profile in a week and the average load profile of all participants during the same week, the type A report pointed out that the household tended to consume much more electricity at night than the average household. From a type A report, recipients received advice that they should attempt an energy-saving morning-oriented lifestyle—with less electricity consumption for air conditioning and lighting at night. The report also stated that a morning-oriented lifestyle is also desirable in terms of the recipients' health [55–57] toward activating (2-3) "other motives" for behavioral changes. The evaluation result by report type implies that (2-3) "other motives" encouraged reduction in electricity consumption.

A type B report also produced a tendency to save electricity, but the magnitude was smaller than with type A. A type B report was sent to households that consumed less electricity when they followed their ordinary lifestyle. From a comparison between the household's daily load profile with the typical load pattern and that of the consuming load pattern, the type B report pinpointed the dates and times when each household consumed much more electricity than with its ordinary lifestyle. This feedback helped recipients reflect on their daily life and find some causes of a spike in electricity usage, toward activating the recipients' own (2-1) "personal norms". The evaluation result by report type indicates that the average feedback effect with type B was minute. However, the result by household suggests that a household decreased its electricity consumption if its daily average electricity consumption with the typical load pattern before the feedback was high and the consumption in the consuming load pattern was much higher than that of the typical load pattern. These results imply that information about major differences between the typical load pattern and consuming load pattern encouraged recipients to activate their personal norms, thereby reducing their electricity consumption.

The following points should be noted for future research. It is important to develop a mechanism that avoids unintended consequences, such as the boomerang effect. The results of the lumped evaluation with seven explanatory variables (Table 4) indicate that daily electricity consumption increased significantly after a household read the message "In August, you consumed (considerably) less electricity than the average household" from the report ($X_{it}^{below\_average}$); this effect was stronger than the other effect (X_{it}^{read}). Some experimental studies have addressed the control of such unintended consequences [7,35,36], and they found that adding an injunctive component to the message could reduce the boomerang effect. Well-designed methods of providing information can enhance the effect of tailor-made feedback.

The use of various sensor technologies and advanced data analysis technologies should also be advantageous in improving feedback. With this pilot program, aggregated electricity load profiles were analyzed to identify household lifestyles. More detailed features of the residents' behavior could have been investigated if electricity-use data for each appliance could have been obtained. It may be expedient to measure residents' quality of life by collecting their physical data using wearable devices. Improvements in the data analysis method are also important for practical tailor-made feedback. Two analytic methods (frequency analysis and cluster analysis) were used to detect the features of residential load profiles. An advanced analytic method, such as deep learning, should be employed in future to deal with massive data on energy consumption. Integrating analysis technologies and sensor technologies will become increasingly important.

It is also essential to conduct a large-scale experiment for wide application of the feedback. Owing to the delay in the spread of smart meters in Japan, the available electricity-use data there at present are scant compared with other OECD countries. Implementing a long-term feedback pilot program with many participants would show the scale effect and prolonged effect of the feedback.

6. Conclusions

Using energy feedback reports based on electricity-use data analysis methods, the feedback effect on household electricity consumption was evaluated in this paper. In a report based on the results of frequency analysis (type A), the recipient's load profile in a week in August was compared with the average load profile of all participants during the same week: it is indicated that the recipient consumed more electricity at night than the average household. The average feedback effect was -0.265 kWh/day with the boomerang effect and -0.726 kWh/day without the boomerang effect. In a report based on the results of cluster analysis (type B), the typical load pattern and consuming load pattern of each household were compared: it is stated that recipients consumed less electricity when they followed their own ordinary lifestyle. The average feedback effect here was +0.182 kWh/day with the boomerang effect and -0.084 kWh/day without the boomerang effect. Recipients significantly reduced their electricity consumption if their daily average electricity consumption with the typical load pattern before the feedback was high and their daily average electricity consumption with the consuming load pattern was higher than that of the typical load pattern. From a questionnaire survey on the feedback reports, it is found that tailor-made feedback was beneficial for over 80% of recipients.

For the purposes of demand-side management, the Japanese government has required that power companies install smart meters in all households by the early 2020s. However, few studies have examined feedback about a household's energy consumption and its own lifestyle [2]. This pilot program using tailor-made feedback demonstrated how to promote energy-conservation measures among Japanese residents, which hitherto has been insufficiently developed. In this pilot program, it is found that tailor-made feedback—corresponding to a household's lifestyle—is necessary among many households. It is also found that this feedback had an effect on reducing electricity consumption.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Regression analysis result (fixed effects model, type A).

	Six Variables		Seven Variables	
	Coefficients	**Standard Errors**	**Coefficients**	**Standard Errors**
X_{it}^{cool}	1.016 ***	0.048	1.017 ***	0.048
X_{it}^{heat}	0.550 ***	0.106	0.556 ***	0.106
X_{it}^{humid}	0.033 ***	0.003	0.033 ***	0.003
X_{t}^{holi}	0.418 ***	0.104	0.417 ***	0.104
X_{it}^{time}	0.045	0.110	0.045	0.110
X_{it}^{read}	−0.265	0.376	−0.726	0.503
$X_{it}^{below\_average}$			1.407 ***	0.523
Adj. R-squared	0.3796		0.3804	

*** $p < 0.01$.

Table A2. Regression analysis result (fixed effects model, type B).

	Six Variables		Seven Variables	
	Coefficients	**Standard Errors**	**Coefficients**	**Standard Errors**
X_{it}^{cool}	0.909 ***	0.035	0.909 ***	0.035
X_{it}^{heat}	0.497 ***	0.082	0.499 ***	0.081
X_{it}^{humid}	0.032 ***	0.003	0.032 ***	0.003
X_{t}^{holi}	0.191 **	0.085	0.190 **	0.085
X_{it}^{time}	0.017	0.076	0.017	0.076
X_{it}^{read}	0.182	0.210	−0.084	0.291
$X_{it}^{below\_average}$			0.504	0.409
Adj. R-squared	0.3392		0.3393	

** $p < 0.05$; *** $p < 0.01$.

Table A3. Regression analysis result (fixed effects model, type C).

	Six Variables		Seven Variables	
	Coefficients	**Standard Errors**	**Coefficients**	**Standard Errors**
X_{it}^{cool}	0.897 ***	0.046	0.897 ***	0.046
X_{it}^{heat}	0.667 ***	0.177	0.658 ***	0.177
X_{it}^{humid}	0.046 ***	0.005	0.046 ***	0.005
X_{t}^{holi}	−0.008	0.100	−0.008	0.100
X_{it}^{time}	−0.044	0.122	−0.045	0.122
X_{it}^{read}	0.507	0.461	−0.046	0.753
$X_{it}^{below\_average}$			1.062	0.842
Adj. R-squared	0.3611		0.3615	

*** $p < 0.01$.

Nomenclature

Subscript	Unit	Description
i		Household
t		Day
t_i^{read}		Date when household i read a feedback report
Regression Parameter	**Unit**	**Description**
α_i		Intercept (individual effect)
α		Constant term of individual effect, used in the random effects model
ν_i		Error term of individual effect, used in the random effects model
σ_ν^2		Variance of the error term ν_i
β_k		Parameter of kth independent variables
β_{cool}	(kWh/day)/degree C	Parameter of explanatory variable representing space cooling demand
β_{heat}	(kWh/day)/degree C	Parameter of explanatory variable representing space heating demand
β_{humid}	(kWh/day)/%	Parameter of explanatory variable representing daily average humidity
β_{holi}	kWh/day	Parameter of dummy variable representing whether day t was a weekday or holiday
β_{time}	kWh/day	Parameter of dummy variable representing change in household electricity consumption over time
β_{read}	kWh/day	Parameter of dummy variable representing feedback effect on household electricity consumption
β_{eff}	kWh/day	Parameter of dummy variable representing the boomerang effect of the feedback report on household electricity consumption
$\hat{\beta}_{readB_i}$	kWh/day	Estimated parameter of dummy variable representing feedback effect of a type B report on electricity consumption of household i
β_{Etyp}		Parameter of daily average electricity consumption of a typical load pattern in August
β_{Emost}		Parameter of daily average electricity consumption of a consuming load pattern in August
β_R		Parameter of ratio of electricity consumption of the typical load pattern and consuming load pattern
$\boldsymbol{b}$		Vector notation of the parameters
$\hat{\boldsymbol{b}}_{fe}$		Vector notation of the estimated parameters with the fixed effects model
$\hat{\boldsymbol{b}}_{re}$		Vector notation of the estimated parameters with the random effects model
$\hat{V}\left(\hat{\boldsymbol{b}}_{fe}\right)$		Covariance matrix of the estimated parameters with the fixed effects model
$\hat{V}\left(\hat{\boldsymbol{b}}_{re}\right)$		Covariance matrix of the estimated parameters with the random effects model
ε_{it}		Error term, $\varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right)$
σ_ε^2		Variance of the error term ε_{it}
H		Hausman test statistic
Regression Variable	**Unit**	**Description**
$Eday_{it}$	kWh/day	Daily electricity consumption
$Eday_{typ_i}$	kWh/day	Daily average electricity consumption of a typical load pattern in August
$Eday_{most_i}$	kWh/day	Daily average electricity consumption of a consuming load pattern in August
R_i		Ratio of electricity consumption of the typical load pattern and consuming load pattern
$TEMPoa_{it}$	degree C	Daily average outside air temperature
$\boldsymbol{x}_{it}$		Vector notation of the independent variables
X_{it}^k		kth independent variable (explanatory variable)
X_{it}^{cool}	degree C	Explanatory variable representing space cooling demand
X_{it}^{heat}	degree C	Explanatory variable representing space heating demand

X_{it}^{humid}	%	Explanatory variable representing daily average humidity
X_{t}^{holi}		Dummy variable representing whether day t was a weekday or holiday
X_{it}^{time}		Dummy variable representing change in household electricity consumption over time
X_{it}^{read}		Dummy variable representing feedback effect on household electricity consumption
$X_{it}^{below\_average}$		Dummy variable representing the boomerang effect of the feedback report on household electricity consumption
Y_{it}		Explained variable

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