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Determinants of household electricity consumption savings: A Latvian case study

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Abstract. In order to assess the potential for energy efficiency in households it is important to understand the implications for household electricity consumption by analyzing the factors that impact consumption. Moreover some recent studies suggested that changes in household electricity consumption are more likely to be explained by user behavioural aspects than technical solutions. This paper examines the influence of household's personal, demographic, socio–economic, the stock and use of electrical appliances, structural characteristics, external factors (such as weather, location etc.) by analysing data obtained from a smart metering pilot project currently being implemented in 500 Latvian households. The preliminary results show a decrease of the electricity consumption in 2013 (April–December) by 23% for the target group and 5% for the control group. The aim of the study is to introduce a novel model for assessing electricity consumption and savings achieved in households. The main tasks of this study is to examine the main characteristics determining electricity consumption savings, in particular, to evaluate the extent of smart metering influence on electricity consumption savings by using linear regression model.

Key words: Smart metering, electricity consumption, linear regression, energy efficiency.

INTRODUCTION

Notwithstanding the benefits of increased demand response activities in the past years, residential electricity consumption is still rising. In the EU Member States residential electricity consumption increased by 3.6% between 2009 and 2010 thus accounting for 29.71% of total final electricity consumption in the year 2010 (Energy Bertoldi, 2012). In 2012 residential buildings consumed 26% of the total final electricity consumption in Latvia (Central Statistical Bureau of Latvia). Therefore residential sector is the third most consuming sector after the commercial and public sector with 41% and industry and construction with 29%. Electricity consumption for appliances unit consumption per dwelling in Latvia has increased by 35.4% from year 2000 to 2010 (ODYSSEE, 2012). As a main reason of increased electricity consumption was mentioned growing number of appliances utilized in households (e.g. freezers, washing machines, dishwashers, PCs and other small appliances).

Several studies have assessed that electricity demand by households is expected to increase over the next 20 years – during period up to 2020 electricity demand in residential sector is expected to increase 1.5% annually, then decreasing to 0.7% annual growth after 2020 contributed by energy efficiency improvements in appliance design and other energy efficiency measures (European Energy and Transport 2030 report). Therefore, detailed planning and execution of demand–side energy efficiency programs is needed to reduce residential electricity consumption in order to meet obligations concerning improvements in energy efficiency for end users. Smart metering systems have been identified as a promising pathway by promoting energy efficiency in households (JRC, 2012, Ernst & Young, 2012).

Many European countries are only just now getting started with smart meter roll–outs. 10% of the EU households have smart meters, but they are being deployed rapidly to meet a mandate that 80% of the EU households should be provided with smart meters by 2020 (DIRECTIVE 2009/72/EC; JRC, 2012). Starting from April 1st, 2013 Latvia is carrying the first medium scale smart metering pilot project 'Promotion of energy efficiency in households using smart technology' launched by JSC 'Latvenergo' within which 500 smart meters are installed in households by replacing old analogue electricity meters. In total there are around 1 million households in Latvia, which means that only 1% of total electricity customers have been approached (Ernst & Young, 2012). Other objectives within this project have been discussed already previously (Laicane et al., 2013a; Laicane et al., 2013b; Laicane et al., 2013c). When looking at Latvian situation in long term, still there is no strategy either for smart metering diffusion in the market, nor legislation, as well as any vision for much greater roll–out.

Up to now, preliminary results of the pilot project are quite surprising. Total electricity consumption of the target group in 2013 (April–December) was 4,649 MWh. In the meantime the total electricity consumption of 500 control group households (i.e., the reference group without smart meters which was established with the aim to compare result before and after the project) was 3,664 MWh. The results show a significant decrease of electricity consumption by 23% for the target group and 5% for the control group in 2013 (April–December). The results in monthly scale are presented in Fig. 1.

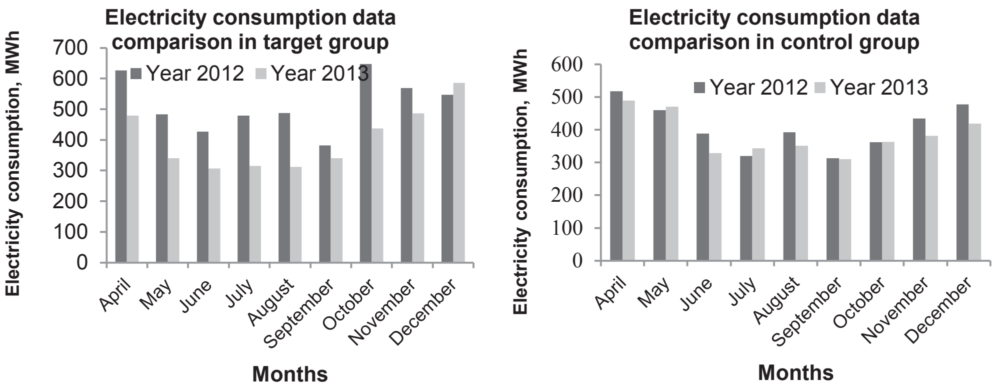

Figure 1. Comparison of electricity consumption in target group and control group households in 2012 (April–December) and in 2013 (April–December).

When looking at these results (see Fig. 1) it is evident that in–depth analysis needs to be carried out in order to explain these results. Understanding of the determinants that drive households' electricity consumption such as personal characteristics (age, gender, education level of residents, and other), floor area, average outside temperature, numbers of occupants, user behavioural factors etc. are needed. As a case study a large data set from project households' is used.

In the following sections a review of methodologies for analysing residential electricity consumption is performed. Factors influencing household electricity consumption are analysed. Based on the analysis of influencing factors a novel model for household electricity consumption has been presented. Finally, the results of regression analysis are presented and potential causes for the results are described.

MATERIALS AND METHODS

Review of modelling approaches and factors influencing residential electricity consumption

Countless studies have proposed models to explain determinants of residential electricity consumption, each of them have their individual strengths and weaknesses. Three approaches, namely top–down, bottom–up engineering and bottom–up statistical regression models are the most commonly used. In the early studies bottom–up models was used for adopting an econometrics perspective attempting to explain aggregate consumption data based on a selected stock of appliances. Therefore, the effect of behaviour and other variables such as climate are merged with the effect of appliances thus minimizing the amount of data requirements for end use consumption estimation (Aydinalp et al., 2003; Swan & Ugursal, 2009). Other studies explained the decision making process of the households, explaining how the consumers respond to changes in price and analyzing only a partial set of residential electricity consumption determinants, e.g., appliance stock, weather conditions or behavioural factors (Cayla et al., 2011; Sütterlin et.al., 2011).

Different linear regression models were used in several studies by assessing the statistically significant variances associated with electricity consumption. Changes in electricity consumption are affected both on the specific variables and conditions behind it, as well as the interaction to each other. The analysis of literature shows that there are many factors that affect residential electricity consumption. A review of studies analysing influencing factors and their impact on electricity consumption is summarized, as shown in the following Table 1.

As indicated above major categories determining household electricity consumption are users' personal, socio–economic factors, physical characteristics of the building, weather and location, appliance stock, occupancy and occupants' behaviour towards energy consumption. Through the review modelling approaches it can be found that the most frequently used factors in describing changes in electricity consumption are: housing type, household income, electrical appliance holdings and number of occupants. Strong correlations among these factors with each other, thus another task is to evaluate correlations among independent variables.

Table 1. A summary of influencing factors and their impact on electricity consumption

Factors	The impact on electricity consumption (analysis of literature)
1. Residents' personal characteristics: • *Age* • *Gender (female/male)* • *Education level* • *Marriage status* • *Family size and composition (the number of people living in household (i.e., occupancy)*	Residential electricity use rises with age (Sardianou, 2007; McLoughlinet al., 2012; Chen et al., 2013; Kavousian et al., 2013; Zhou & Teng, 2013). For households with household heads older than 50 years, electricity consumption is higher by approximately 3% (Zhou & Teng, 2013). If age of people increase, energy saving actions decreases (Carlsson–Kanyama et al., 2005; Linden et al., 2006; Sardianou, 2007) and opposite results found Chen et al., 2013. Some studies found different behaviour between men and women (Bar et al., 2005; Hunter et al., 2005), but another studies found that respondents' gender, educational level and marital status are not significant variables affecting electricity consumption and saving activities (Sardianou, 2007). Families with higher education have higher electricity consumption than middle or lower classes (Santamouris et al., 2007; McLoughlinet al., 2012; Zhou & Teng, 2013). Household electricity consumption increases by approximately 8% points for every additional family member (Zhou & Teng, 2013). Adults living with children consume considerably more electricity than those living alone or with other adults (Bartusch et al., 2012; McLoughlinet al., 2012).
2. Residents' socio–economic factors: • *Household monthly income* • *The share of household's expenditures for electricity consumption* • *Electricity price* • *Rebound effect*	Higher income households consume more electricity (Carlsson–Kanyama et al., 2005; Linden et al., 2006; Santamouris et al., 2007; Vringer et al., 2007; Filippini, 2011; Theodoridou et al., 2011; Zhou & Teng, 2013). Others studies found no significant correlation between electricity consumption and income level (Kavousian et al., 2013). Consumer's private monthly income and electricity expenditures are statically significant variables affecting conservation altered behaviour (Poortinga et al., 2003; Sardianou, 2007). More affluent households have more energy–efficient appliances on average (Kavousian et al., 2013) and live in new constructions (Theodoridou et al., 2011). An increase in electricity price by 10% reduction in demand by 4.5 % can be observed (Kilian, 2007). Some studies estimated that in some cases rebound effect leads to an overall increase in energy consumption by 5–15% (Druckman et al., 2011).
3. Stock and holdings of electrical appliances: • *Stock of electrical appliances* • *Frequency of use* • *The share of energy efficient appliances*	More electric appliances lead to a high growth of electricity consumption (Ouyang & Hokao, 2009, Zhou & Teng, 2013). Older households have fewer household appliances than younger households (Carlsson–Kanyama & Linden, 2007). In some cases home appliances account for over three quarters of total household electricity consumption (Murata et al., 2008). More frequent use of appliances leads to higher electricity consumption (Kavousian et al., 2013). The existence of energy efficient appliances is associated with lower power consumption (Sardianou, 2007; Al–Ghandoor et al., 2009; Ouyang & Hokao, 2009; Theodoridou et al., 2011; McLoughlinet al., 2012; Bartusch et al., 2012; Sanquist et al., 2012; Chen et al., 2013; Kavousian et al., 2013; Zhou & Teng, 2013).
4. Household structural characteristics: • *Type of housing*	In general, electricity consumption by dwellings is higher than in apartments (McLoughlinet al., 2012; Kavousian et al., 2013). Households residing in detached houses are more willing to engage in energy conservation activities than those living in apartment (Sardianou, 2007). Larger dwelling size results in higher household electricity consumption

• *Household size in m2* • *Household age* • *Electrical heating type* • *Indoor temperature maintained during winter time and summer time*	(Yohanis et al., 2008; Bartusch et al., 2012; McLoughlinet al., 2012; Zhou & Teng, 2013). A significant variance in electricity consumption has been established in households with electrical heating system (Theodoridou et al., 2011; Bartusch et al., 2012). Older houses are less energy efficient (O'Doherty et al., 2008), in contrary other studies found that older houses has no significant impact on electricity consumption if compared to younger ones (Kavousian et al., 2013). Newer buildings are better insulated and have energy–efficient lighting installed compared to older buildings resulting to electricity consumption reduction (Abrahamse et al., 2005; Linden et al., 2006; Kavousian et al., 2013). In some studies it was found that mean indoor temperature in wintertime does not significantlly affect electricity consumption (Wiesmann et al., 2011).
5. Residents' behavioural factors: • *The effect of information* • *Knowledge / awareness / attitude level on electricity consumption*	Recent studies reported savings in the ranges of 5–15% when evaluating the effects of feedback information on electricity consumption (Darby, 2006; Burgess & Nye, 2008; Fischer, 2008; Gyberg & Palm, 2009; Ouyang & Hokao, 2009; Darby, 2010; Hargreaves et al., 2010; Vassileva et al., 2012). Some studies show higher effect, i.e., 22% (Jensen, 2003) or lower effects, i.e., – 4.5% in Austria (Schleich et al., 2013), 3% in Denmark, (Gleerup et al., 2010), 2.7% in US (Allcott & Mullainathan, 2010). Consumers' income, family size positively affect energy conserving actions, but expenditures and age of the respondent are negatively associated with energy conserving actions that a consumer is willing to adopt (Sardianou, 2007).
6. Other factors: • *Location, geographic area* • *weather characteristics*	Location of household may contribute by up to 46% to the variability in consumption (Kavousian et al., 2013). Significant relationship between external temperature and electricity consumption that tended to be stronger during periods of cooler weather can be observed (Parker, 2003; Hart & de Dear, 2004). Ouyang & Hokao, 2009 found that change in temperature by 0.8°C can significantly increase electricity consumption.

Household electricity consumption model

Model setup

A novel model for assessing factors that determine electricity consumption savings and electricity use in households has been proposed as shown in Fig. 2. Conceptual foundation of the model is developed based on modelling the relationships between people's individual choice, household's energy profile and external factors for determining savings. The idea of the model is to contextualize household electricity use to find out how do households inhabitants, activities and appliances together determine behaviour.

The model is build on the basis of: a) classification of independent variables (households personal, demographic, socio–economic, the stock and use of electrical appliances, structural characteristics, external factors (such as weather, location etc.), b) implementation of smart metering as an energy efficient measure; c) understanding and selection of interaction among independent variables to each other and with electricity consumption.

Investigation of households' individual choice characteristics are based on people's individual choice theories found in previous studies (Gadenne et al., 2011; Lingyun et al., 2011; Wang et al., 2011; Wenshun et al., 2011; Poortinga et al., 2012; Bamberg, 2013; Klockner, 2013; Webb et al., 2013).

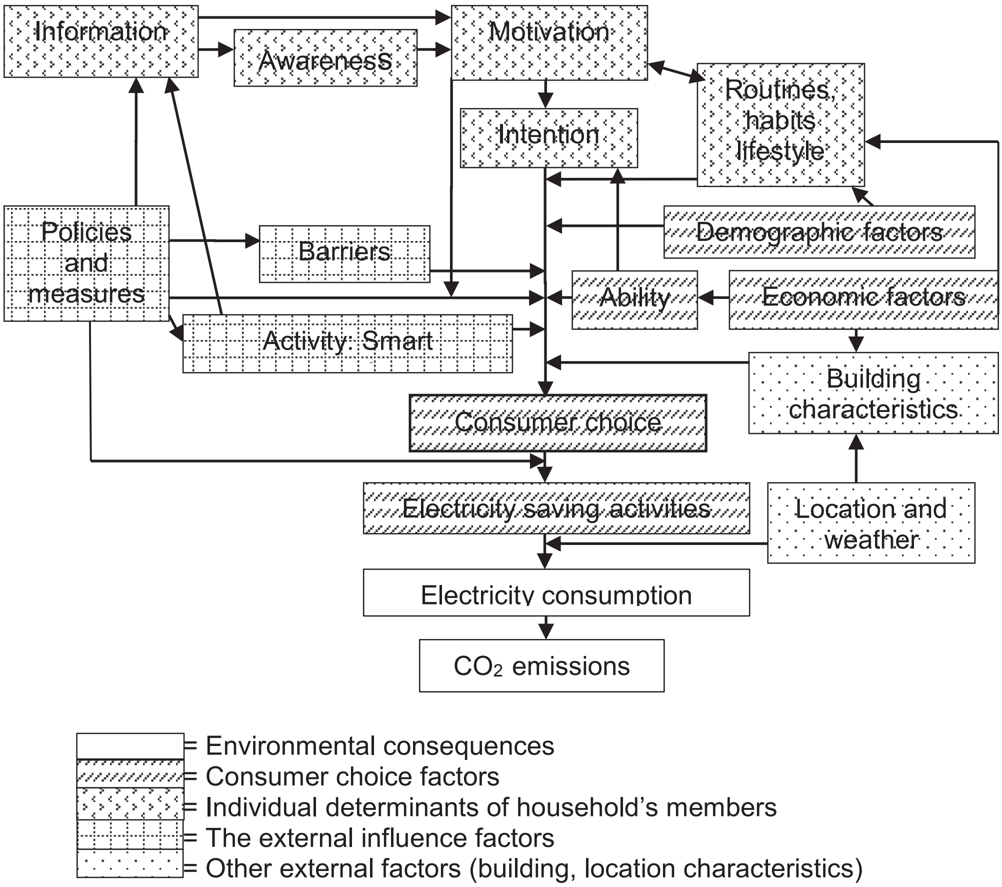

Figure 2. Model of assessing household electricity consumption.

In this model individual determinants of household's members include predisposing factors, information, awareness, motivation, routines, habits, lifestyle and intention. Predisposing factors are behaviour, psychological factors, biological and social–cultural factors. Information is related to respondent's personal factors, as well as source and channels of information provided. Awareness is resident's knowledge, cues to action and possibilities for risk perception and other factors. Motivation is defined like residents attitude towards energy savings, including consideration of Pros & Cons, rational & emotional thinking, as well as motivation depends on social influence, including social norms and public pressure. Resident's are also determined by daily routines, habits and lifestyle factors. As a result, intention is formed based on precontemplation, contemplation and preparation to act. Consumer choice determinants used in the model are defined as economic factors (income level, expenditure pattern etc.), demographic factors (residents' age, gender, education level, number of persons in household etc.), and users' abilities (action plans and skills) that finally determines household choice. The external environment are defined as smart metering implementation in household (related to design and feedback activities for consumer involvement in energy efficient measures), policies and measures (regulations regarding final energy consumption reduction targets and smart metering and subsidies for consumers), barriers for smart metering adoption, as well as building characteristics (type of housing, number of rooms, area in m^2, heating system etc.) and location and weather characteristics (geographic area, heating degree days or cooling degree days).

We consider that environmental consequences occur due to the impact and interaction of individual determinants of household's members, consumer choice decisions, as well as external environment. Household's energy profile have been constructed based on integrated approaches for household energy analysis and energy use reflecting buying, maintenance and usage decisions of electrical appliances (Xu et al., 2008; Gadenne et al., 2011; Kowsari & Zerriffi, 2011; Oltra et al., 2013; Yue et al., 2013). At the end environmental consequences are stock and use of electrical appliances and electricity saving activities resulting in household electricity consumption and CO_2 emissions.

In the model, in particular, we focused on links between the interventions: smart metering, feedback/information and other variables. With the data available, the purpose of the study is to examine a part of the model, in particular:

a) to investigate the main characteristics determining electricity consumption savings by testing all variables that can be observed and measured;
b) to evaluate the impact of smart metering on electricity consumption savings;
c) to assess the interaction of independent variables with each other.

Regression analysis

As mentioned before project households' consumption in 2013 were lower than in 2012 both in target group and control group. The variation in household electricity consumption depends on the various households' aspects. In order to explain the factors that influenced changes in consumption, as well as to assess the impact of smart metering a separate linear regression model for smart metering and other independent variables were developed. We assume, that those determinants whose contribution to electricity savings has a linear relationship with electricity savings. The regression model is given by the following equation:

$$y_j = \beta_{0j} + \sum_{i=1}^{M} \beta_{ij} X_{ij} + \epsilon, \quad (1)$$

where y_j is the electricity consumption savings in kWh of household j (difference in electricity consumption in 2012 and 2013); β_{0j} is is a constant; X_{ij} is the value of the determinant for household j; β_{ij} is the regression coefficient for that determinant; M is the total number of variables (household features); ϵ is the error term.

Data summary, explanatory variables and pre-processing

For our analysis we used electricity consumption data in 2012 and 2013 normalized by annual consumption. Before the implementation of smart meters, the majority of target group and control households paid for electricity using self declaration method (monthly self–reading and payment). When looking at consumption data in 2012, it was found that most of households made irregular payments during the year 2012. A large part of them paid for electricity just once or twice per year or made the payments for almost the same amount of electricity for several months both in winter and in summer. Another lack of data was that a large part of households made payments according to adjusted payment plan (payment of equal monthly consumption rate through the year). Thus the following historical payment data does not reflect the actual monthly consumption. Self-declaration method and payments according to adjusted payment plan method are not really appropriate and suitable for the analysis of consumption data directly. Therefore we use an additional electricity consumption data set of meter readings in 2012 conducted by electricity supply company (JSC 'Latvenergo'). Electricity consumption data in 2012 were normalized based on consumption data from the meter reading during 2012 multiplied by 365 days and divided by the number of days between the last and the first meter reading during 2012.

As mentioned above, control group households are not equipped with smart meters. Also most of control group households pay for electricity using self declaration method and payment plan method. Likewise, we use an additional electricity consumption data set of control group households' meter readings in 2013 which was obtained from electricity supply company making a similar data normalization as in 2012. Much better situation is regarding to target group data. Here consumption data were obtained from smart meters during 9 months (April – December, 2013), i.e. – 275 days. Therefore, electricity consumption of target group in 2013 were normalized by multiplying smart metering data for 9 months period with 365 days and divided by 275 days.

Empirical data analysis (i.e., regression analysis) is supported by an extensive household survey and electricity consumption data in the period from year 2012 to 2013. A large data set both for the target group and the control group were taken from the survey responses carried out at the beginning of the project in April – May, 2013. Responses of 729 households were available from this survey of which 429 belonged to the target group and 500 to the control group. The household survey includes questionnaire about the occupant's personal, socio–economical, dwelling characteristics, electrical appliance stock, occupancy and occupants' behaviour towards energy consumption and other information (see Table 1 in Laicane et al., 2013a). Sequentially, the set of 267 variables is established on the basis of data obtained from survey. First, we aim to assess the effect of smart metering based on electricity consumption savings achieved in 2013 both in the target group and the control group. Selection of cases was based on consumption data available for both years – 2012 and 2013. For 13 target group households' and for 379 control group households consumption data in 2012 and 2012 and/or 2013 were not available, respectively. These cases were removed from the subsequent analysis of smart metering effect on electricity consumption savings. Finally, 537 cases were selected for the analysis. Second, we used aggregate consumption data of 2013 in order to assess the main characteristics determining electricity consumption savings in 2013 both for the target group and the control group. Due to lack of consumption data in 2013, 359 control group households were removed from the subsequent analysis. None of cases in target group were excluded from analysis. As a result, 570 cases were selected for linear regression analysis.

RESULTS AND DISCUSSION

Preliminary regression analysis results. The effect of smart metering

Statistical analysis for all the computations has been carried out using SPSS 21 data mining and statistical analysis software. The impact of smart metering on electricity consumption savings was evaluated by linear regression model. The significant effects between target group and control group were evaluated by using the independent variable 'group of participance' and dependent variable 'electricity consumption savings in 2013'. It was assumed that all data are normally distributed represented by a dummy variable which takes on the value of 1 if the survey respondent is assigned to target group and 0 if otherwise. Dummy titled 'smart' is supposed to capture the effect of feedback from the smart metering.

The preliminary results indicate that smart metering has a statistically important influence on electricity consumption savings. 21.3% of variance in electricity consumption savings can be explained by the belonging to the group of participance. Higher savings has been achieved in the target group if compared to the control group. This indicates that smart metering is a promising pathway in contributing to electricity consumption savings. This hypothesis is in agreement with previous studies (Haakana et al., 1997, Jensen, 2003).

Preliminary regression analysis results. The effect of various variables

For the purpose to identify the most important determinants of residential electricity consumption and describe the variability among observed, correlated variables, linear regression model was used. Regression analysis was carried out based on the data set of 267 variables – i.e., responses of survey questionnaire. These 267 variables were used as the independents variables, but electricity consumption savings as the dependent variable. The next Table 2 shows the linear regression results and overall fit statistics.

Table 2. The results of linear regression

Model Summary									
R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin–FWatson
				R Square Change	F Change	df1	df2	Sig. Change	
.816	.666	.338	5813.108	.666	2.033	264	269	.545	1.846

From Table 2 it can be concluded that the adjusted R^2 of our model is 0.338 and the R^2 is 0.666. Such high difference can be explained by the large number of variables include in the model (267 variables). It means that the variables included in the linear regression explain only 33.8% variance in electricity savings. Therefore, the most part of variance in electricity savings can be explained by other important variables while not included in this model.

Preliminary results indicate that the variables 'electric gates', electric sauna or electric bath house', 'heat pump' 'solar collectors' and 'group of participance' is among the most statistically significant determinants that positively affect electricity consumption savings (higher positive value of factors indicate the larger savings). We hypothesize that the positive effect on electricity consumption savings by ‘electric gates’, electric sauna or electric bath house’, ‘heat pump’ can be explained by the fact that in general only a small number of households have such electrical devices. Results also indicate that higher energy savings has been achieved in households where solar collectors are installed. The variable ‘type of housing’ (detached house, apartment, other type of residence) has been found as the most statistically significant variable that impact electricity savings achieved by households with a negative sign (higher negative value of factors indicate the decline in savings). That means that greater electricity savings can be achieved in larger detached houses rather than in apartments. Also variables ‘central heating’ and ‘the possession, number and use of LED TV sets’ affect electricity consumption savings with a negative sign. That means – more households have central heating and LED TV sets, less electricity savings achieved. However, together these variables explain only 17% variance in electricity consumption savings. The greater part of variance in electricity consumption savings therefore can be explained by other variables.

One of the tasks within this study also was to assess the interaction of independent variables with electricity consumption savings and their correlation to each other. It allows determining if the main effects are independent of each other. For this purpose correlation matrix obtained from the preliminary regression analysis were investigated. First, it is important to look at the t values for single independent variables in order to assess the extent of significance of individual variables. In most cases t values for a single independent variables are low that indicate that there are high correlation among variables. Correlations among variables are described below. It the model the Durbin–Watson test for auto–correlation was included in order to test that the residuals from a linear regression or multiple regression are independent. The Durbin–Watson is 1.846, which is between the two critical values of $1.5 < d < 2.5$ and therefore we can assume that there is no first order linear auto–correlation in the linear regression data. Significant effects between the different variables are evaluated by Kaiser–Meyer–Olkin and Bartlett’s test of sphericity. The Kaiser–Meyer–Olkin selection is appropriate, because a) it is a measure of sampling adequacy tests whether the partial correlations among variables are small and b) it is an index for comparing the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. Bartlett's test of sphericity is used to test the null hypothesis that the variables in the population correlation matrix are uncorrelated. The observed significance level is 0.545.

By analysing the regression coefficients it can be concluded that most of variables have no statistically significant influence on electricity consumption savings. It is also important to notice that 267 variables included in the analysis have a different statistical data type, a part of these variables have a nominal values, ordinal values, or binary values. The number of variables we used is too large for regression analysis and more sophisticated approach is needed to evaluate the most important determinants explaining electricity consumption savings. However, the first predicting correlation results indicate that greater or smaller correlations among different independent variables can be observed. Main high positive and negative correlations among variables are listed in Table 3.

Table 3. Observed correlations among various variables

Variable	High positive correlation	High negative correlation
Group of participance	Iron, cooker hoods, electric kettles and water filtering system	Income, language and gender of respondent
Gender	Electric sauna or electric bath house	Lightning, refrigerator, home cinema system, tablet PC, the average indoor temperature in winter
Age	Analogue TV set, freezers, storage water heaters (boiler)	The number of household members living in the same residence, laptop, dishwasher, electric stove
Number of occupants	Income, average time of staying home, refrigerator, electric kettles, washing machine, electric stove, electric ovens, dishwasher, cooker hoods, analogue TV set, iron, laptop, energy–saving light bulbs	Type of housing, the average degree of education in family, residents age, central heating from energy supply company
The average degree of education in family	Age of respondent, electric sauna or electric bath house, use of washing machines together with a dryer, vacuum cleaners	Occupancy, average time of staying at home
Type of housing	Insulated exterior walls and roof	Income, occupancy, average time of staying at home, refrigerator, freezer, electric stove, electric sauna or electric bath house, storage water heater (boiler), heat pump
Household area	Year of construction, solar panels, acoustic sound systems or music centres, air humidifiers	No significant negative correlations
Year of construction	Household area, central heating from energy supply company, insulated exterior walls, roof	Dishwasher, electric gates, the average indoor temperature in winter
Electrical heating	The use of electric heaters, electric under floor heating system, electric stove together with electric oven, storage water heater (boiler)	Natural gas heating
Income	The number of occupants, household type, electric stove, cooker hoods, dishwasher, laptop, natural gas heating	Central heating from energy supply company

Whereas, relatively high correlations are observed among the independent variables indicating that these variables are not really independent from each other and some common factors can be found behind them. Some have high logical interdependencies or high statistical correlation. That's why a regression with all variables leads to only few statistic significances.

More data are needed to validate some of the findings of this paper. Specifically, household data from a more heterogeneous sample over a larger period of time are needed for validating the generality of smart metering effect on electricity consumption savings. Re–surveying would be advisable in order to gain information about major changes in households during the first year of the project, for example, whether household income, composition has been changed or new electrical appliances purchased etc. during this time. Re–surveying At the beginning of the project re–surveying was planned in April–May, 2014, however up to now, is not clear, whether it will take place in planned timeframe.

Some of the further tasks will be also to test, whether electricity demand will be significantly influenced by socioeconomic factors or it is more dependent on changes in the building characteristics, user behavioural factors or electricity price.

Currently, electricity price for households is regulated by Public Utilities Commission and is 11.64 euro cents per kWh up to 1,200 kWh (start tariff) and 15.15 euro cents per kWh when 1,200 kWh level is exceeded (basic tariff). According to electricity market opening conditions all electricity users, including households, need to buy electricity on the open market. Households consume about 25% of all electricity use In Latvia. In April1st, 2014 it was planned to open the electricity market for households, however, the Latvian government decided to postpone the opening of electricity market for households until 1st January, 2015. It is expected that with the opened electricity market, electricity price could rise by up to 40%. Therefore further steps of analysis will be also to assess whether increase in electricity price result in lower electricity consumption.

CONCLUSIONS

The rationale of this study is a part of smart metering case study in Latvia. The preliminary results show a decrease of electricity consumption by 23% for the target group and 5% for the control group in 2013 (April–December). In order to gain a first impression of what factors directly affected the reduction in electricity consumption, a novel model for assessing household electricity consumption has been proposed. The aim of this model was to understand how households' inhabitants, activities and appliances together determine electricity consumption and savings. This model will be further improved by including all possible influences and interlinkages in order to analyze the results of the project, by differentiating between consumption and savings model. The potential follow up of this research will be to develop a subset of hypothesis to be tested in order to find out the most significant factors affecting electricity consumption and electricity saving actions.

As indicated in recent literature appropriate energy efficiency measures for reducing energy consumption can be designed and implemented based on the influencing factors that determine household electricity savings. Understanding of interactions among different factors (e.g., the relationship between weather, appliance load, lighting load, and heating load) offer considerable potential for improving energy efficiency (Abrahamse et al., 2005).

Based on data available up to now a part of the model has been tested by using a set of an extensive survey of household data and electricity consumption data of 2012 and 2013. The main tasks were to evaluate the extent of smart metering influence and influence of other main factors that determine electricity consumption and savings. Linear regression model was used for this purpose. The preliminary linear regression results indicate that belonging to the target group seems to have a strong, statistically significant influence on consumption and savings by explaining 21.3% of variance in electricity savings. Smart metering matters need to be further developed. The inclusion of other variables in the linear regression model (267 variables in total) showed that only 33.8% variance in electricity savings can be explained with these variables. Therefore, the most part of variance in electricity savings can be explained by other important variables while not included in this model. Thus adequate regression analysis (taking into account that there are metric, ordinal and binary variables as independent variables) with a smaller number of more significant variables need to be carried out by evaluating to which extent the assumptions of the respective regression model applied are valid. In addition, with the data available it might be better to explain household consumption rather than savings.

When assessing the interaction of independent variables with electricity consumption savings and their correlation to each other, relatively high correlations among variables were found. It indicates that these variables are not really independent, but there are some common factors behind it. The number of variables included in analysis is too large and more sophisticated approach is needed to evaluate the most important determinants explaining electricity consumption savings. A potential follow–up to this study is to find the most appropriate methodology for reducing the number of variables by extracting the correlated variables to more independent ones. Identifying of independent variables and factors behind them can be developed by using factor analysis, principal component analysis and logical derivation from the model.

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