Socio-Technical Analysis of Energy Demand Behaviour and Energy Consumption of Households Equipped with Smart Home Systems

T. Rehm
Cologne Institute for Renewable Energy (CIRE)
Faculty of Process Engineering, Energy and Mechanical Systems
University of Applied Sciences Cologne, Cologne, Germany
e-mail: Tobias.rehm@th-koeln.de

Second T. Schneiders*, R. Etzkorn*
Cologne Institute for Renewable Energy (CIRE)
Faculty of Process Engineering, Energy and Mechanical Systems
University of Applied Sciences Cologne, Cologne, Germany
e-mail: Thorsten.schneiders@th-koeln.de

ABSTRACT

German energy and climate policy pursues the goal of reducing greenhouse gas emissions in the long term. So that politics, industry and research institutes can find suitable strategies in this respect, information is needed on changes in the energy demand behaviour of final consumers. This paper analyses the energy consumption of 120 households equipped with smart home. It is examined whether statements about the participants and their environment can be made on the basis of the energy consumption (heat and electricity). In addition, the change in energy demand behaviour due to the use of smart home systems is analysed. For this purpose, the raw data of the field study will first be validated. Subsequently, procedures as well as methodologies, taking into account data sciences and analytics, are presented, which are used to visualize and analyse the energy consumption data. An outlook shows potentials for further studies in this field.

KEYWORDS

Smart Home, Data Analytics, Field-test, Households, Heating Consumption, Electricity Consumption

INTRODUCTION

Germany's climate protection targets for 2030 are to produce 55% less greenhouse gas emissions than in 1990 [1]. The private household sector accounts for 26.2% of Germany's total energy consumption. Furthermore, the largest share is space heating, which accounts for almost 70% (corresponding to approx. 1,663.83 PJ or 462.175 TWh) of final energy consumption in private households [2].

In addition to classic energy saving measures for buildings, such as insulation or the use of efficient renewable energy technologies, home automation can also be used. Here, ICT and IoT technologies are used to use energy in the household at the times when it is needed. In home automation, for example, existing components will be expanded with the help of communication modules, thus establishing networked systems in the household. This is also known as the smart home. The aim of the smart home is to support the household inhabitants in their daily lives. By intelligently linking actuators and sensors, logical automations can be programmed that facilitate energy management in the household and help save energy. [3]

De facto, the smart home system has not yet established itself in the household sector, and several studies have already investigated this. For example, a study with 14 households in the USA in 2011 reveals that the broad acceptance of the smart home depends on four points, these are high operating costs, incompatibility, poor handling and security [4].

On the other hand, there are only a few statements on energy saving effects through smart home technology. From a study on smart thermostat systems in existing buildings, it is possible to work cost-efficiently in a single-family home with savings of 5.7%. Therefore, thermal building efficiency and energy savings are key factors for cost efficiency [5].

In recent years, some smart home field-tests were carried out focusing on the technical functionality, several system applications or the user behaviour and acceptance issues [6]. The field-test ‘SmartHome Rösrath’ carried out by the research team at University of Applied Sciences Cologne (TH Köln) focused on the main research question whether smart home systems enable savings on heating costs and the socio-technical aspects of usability and acceptance using smart home systems [7].

Based on heating and electrical building consumption profiles, conclusions can be drawn on specific data of the inhabitants and their environment and changes the energy demand behaviour in the heating and electricity sector in households is influenced by the use of smart home technologies?

The aim of this paper is to find correlations between the power consumption of and the specific data of these and their environment. Further, the change of the energy demand behaviour by smart home systems is to in existing buildings are analysed. For the analyses, methods and procedures relating to data sciences and data analytics.

In this context, this paper summarizes the research study and the most important data sets of the field-test 'SmartHome Rösrath'. In the following, therefore, the existing materials collected during the field-test and the evaluation methodology used are presented. In the next main chapter the results are described. Finally, the results are reflected in a discussion and summarized in a conclusion.

MATERIALS AND METHODS

In this chapter, the existing the field-test itself are presented and data sets of the field-test. In addition, the evaluation methodology for evaluating the data sets is described.

Setup of the field-test

This paper based on the results of an applied smart home field-test with 120 households from 2015 until the end of 2017. The private building sector has high-energy consumption, especially for heating. Therefore, the study examined the use of smart home systems to increase energy efficiency in residential buildings with a focus on heating. Furthermore, it is examined what influence the smart home system has on electrical power consumption.

The selected households are representative in terms of the age structure, of the inhabitants and other demographic and psychographic variables. They were equipped with smart home systems to control the room heating (e.g. with remote-controlled heating valves, window contacts) combined with programmable routines to automatically adjust the settings of the heating systems (e.g. switching off the heating when windows are opened). Other components were measuring and switching plugs for switching electrical consumers (e.g. lights).

A radio-based smart home system was selected for the field-test because it has all the basic functions (features) and components of an intelligent building automation system. For example, the typical fields of application such as energy efficiency, security and comfort can be covered. In addition, this smart home system is a radio-based Plug & Play system. This means that expensive cabling during installation could be avoided.

An app is used to control the smart home system. The app enables the control of actuators (devices), the monitoring of consumption and device states. Furthermore, automations (rules, scenarios and schedules) can be configured in the app. The app can be used on smartphones, tablets or via an Internet browser using a computer. The numbered basic components used in the study are shown below in Figure 1.

1. Smart plug (dimmer, consumption measurement)
2. Smoke detector (alarm siren)
3. Window or door contact
4. Gateway (home base)
5. Heating thermostat
6. Motion detector
7. App (control)

Figure 1. Smart home components used in the field-test

Data basis of the field-test

The existing data basis consists of monthly recorded meter readings on electricity and natural gas consumption. The monthly data sets result in the household consumption of the field-test for one year. Furthermore, consumption data (electricity and heat) of the last three years are available for most households. Previous analyses provide the data basis for the changes in heating energy consumption due to the use of the smart home system. The changes in heating energy consumption are based on previous analyses by comparing consumption data from previous years without smart home and a reference year with smart home [7]. The percentage changes calculated from this (savings and additional consumption) are evaluated in this work by means of cluster analysis. In addition to the already evaluated heat consumption (natural gas), the recorded electricity consumption data are also evaluated using cluster analysis.

A start survey was also used to obtain socio-demographic data on the household inhabitants, such as the number of persons or the level of education. In addition, data on the building, such as age of the building, installed plant technology for heating or possibly electricity production, such as photovoltaic systems. These data sets are referred to as **hard data facts** in the following, as they are based on numerical values.

Monthly surveys of the study participants made it possible to continuously record status data and energy consumption. In addition, quarterly surveys on the user behaviour of the participants were created. There, questions were asked regarding the heating and ventilation behaviour and the energy awareness of the participants. In addition, the participants had to answer questions about the technical components and the app for controlling the smart home system. These data sets will be referred to as **soft data facts** in the following, as they cannot be quantifiably measured with figures, but are based on the subjective opinion of the study participants.
Energy awareness is made up of a sum of questions that were asked to the study participants via a survey. The closed question types (agree fully, agree rather, agree rather not, agree not, no statement) can be used to form a index for energy awareness.
In addition, the participants were also asked about their readiness to recommend to their smart home system. These evaluations were evaluated according to the Net Promoter Score (NPS). The NPS is a method to determine the readiness to recommend products or other services. To determine the NPS, the customers (participants) give a rating of 0 to 10, to express how likely it is that you recommend this product or service [8].

With the help of this data basis, the following analyses of heating and electricity consumption have been carried out.

Methods for data analysis and evaluation

Comparing the reference years with and without smart home systems. The approach for determining changes in heating energy consumption is based on the ratio of average consumption in previous years and the reference year in which the smart home system was used. As well, all heating consumption data were weather-adjusted by the corresponding climate factors of the respective years in order to counteract the effects of the weather, for example, particularly cold heating periods with high consumption.

In the course of the studies, regular interviews and workshops provide valuable insights into the habits of using energy. Electricity and heat consumption data were recorded monthly. To evaluate these data were carried out a comparison between three previous years and with a reference year (with smart home).

Correlation Analysis. A further methodology is the **correlation analysis**. The investigation of correlations between different data and data streams with the aim of finding new value drivers. The evaluation of the data were separated into **hard** and **soft** influencing factors. Quantifiable factors are defined as hard influencing factors. These include the socio-demographic relationships of the residents, the energy demand behaviour, the building equipment and the weather conditions. On the other hand, soft influencing factors are difficult to measure, e.g. subjective assessments and also energy awareness or active use of the smart home system can be defined as such factors.

Data Science Methods. Data science and analytics are used for the methodical evaluation, including cluster analysis (k-means). Data Analytic are the process of data refinement, transformation and extraction of new contexts with the aim of finding value-driving and useful information. [9]
Collecting data and dividing it into groups with similar contexts and contents is called **cluster analysis**. By examining the different groups and finding out the similarities and differences between them, insights can be gained based on the data. Clustering is also called exploratory data collection, because it detects relationships between the individual pieces of information in large amounts of data. With exploratory data collection, it is not possible to predict what will be searched for, only the same patterns will be recognized. One method is the k-Means clustering. By examining the different groups, insights can be gained based on the data. It cannot be predicted what will be searched for, only the same Pattern detected. [10]

Measures of distance and similarity for metric variables (z-standardization). A restriction for the calculation of the Euclidean distance measure is the scale invariance. This describes the absolute sizes of the measured distances between two objects and is dependent on the scale units. Since the Euclidean distance, measure is based on the assumption that the considered dimensions have a comparable scaling; a standardization must first be carried out for a direct comparison of the distances between two variables. This is done by standardizing the measured values (e.g. z-standardization). [11]
Before the measured values can be z-standardized, it must first be checked whether the measurement series follows a normal distribution [12]. The Kolmogorov-Smirnov normal distribution test offers a possibility in this respect. If the series of measurements follows a normal distribution, the z-standardized quantity y_v considered in each case is then formed, taking into account the quotient between the original quantity x_v subtracted with the arithmetic mean value $\bar{x}$ and the standard deviation s_x (see equation 1).

$$y_v = \frac{x_v - \bar{x}}{s_x} \tag{1}$$

The calculation of the arithmetic mean and the standard deviation can be seen in the following equations 2 and 3:

$$\bar{x} = \frac{1}{n} \sum_{v=1}^{n} x_v \tag{2}$$

$$s_x = \sqrt{\frac{1}{n} \sum_{v=1}^{n} (x_v - \bar{x})^2} \tag{3}$$

The result of the standardization is a concrete key figure for the distance between two points or between two objects. The standardization can be applied to all examination units. The resulting key figures can then be summarized in a distance matrix and evaluated using various cluster analysis methods (e.g. k-Means clustering). [11]

RESULTS

In this chapter, the results of the data sets and methods presented in advance are calculated. For this purpose, the evaluation of the heating energy consumption by using the smart home System is carried out at the beginning. The evaluation of the electricity consumption is carried out immediately. For further analysis, electricity and heat consumption are compared in order to show any similarities. Finally, the energy consumption are visualised using the Data Sciences and analytics methods as described in the previous chapter.

Heating consumption – Comparison with previous year consumption figures

The calculations result in a percentage change in heating energy consumption for each participant. The percentage changes for each participant are added up for the entire project. This results in an average change (savings/increased consumption) in relation to the reference year with the use of the smart home system.

The evaluation of heating energy consumption has shown that the maximum savings compared to previous years without the smart home system are around 33%. On the other hand, a maximum additional consumption of a subscriber of 26.5% has been achieved, see Figure 2 [7].

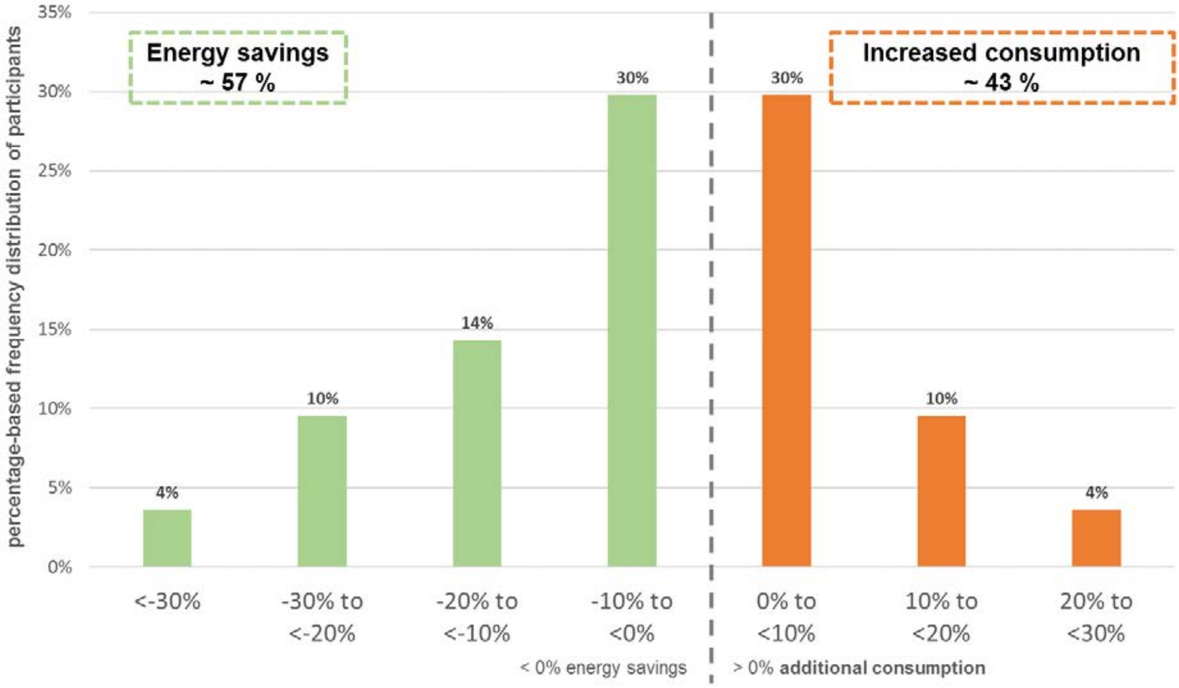

Figure 2. Changes in heating consumption

The following Table 1 contains the most important consumption data regarding the consumption of heating energy. On the one hand, it shows the total heating energy consumption of all participants before and after the Smart Home installation and the difference between the periods. Furthermore, the minimum and maximum consumption of a participant is listed to show the range of the 84 usable consumption data (per household). In the column of absolute differences it is important to know that the differences for the minimum and maximum consumption are composed of the maximum saving and the additional consumption, these also reflect the results from Figure 2. As can be seen graphically in Figure 2, the data is a normal distribution. This also confirms the calculated standard deviation, since 95.45% of all measured values are found in the interval of the deviation +/- two σ sigma from the expected value, see Table 1 standard deviation.

Table 1. Heating energy consumption before and after smart home and standard deviation

	Before Smart Home	**After Smart Home**	**Difference absolute**
All participants consumption	1.956.277 kWh	1.890.642 kWh	65.636 kWh (savings)
Mean per household (n = 84)	23.289 kWh	22.508 kWh	781 kWh
Minimum consumption	4.867 kWh	5.295 kWh	-4.951 kWh (additional consumption)
Maximum consumption	72.190 kWh	75.200 kWh	10.562 kWh (savings)
Standard deviation [δ]	12.387 kWh	11.671 kWh	2.843 kWh

For further analysis of the results, more intensive surveys and discussions on heating behaviour were conducted. It turned out that especially those participants who achieved **higher heating energy consumption** over the duration of the field-test stated the following information in the survey:

- Longer attendance times than at the beginning of the field-test
- Changes in the building and system technology during the field-test period (e.g. incorrectly adjusted heating systems)
- Problems with handling the smart home system

In addition, indications of **rebound effects** were identified. For example, participants indicated:

- "*There is more heating because savings are promised by the smart home system*" or
- "*Heating is made easier by the simpler control of the radiators*".

In the analysis of the participants who achieved **savings** compared to their previous year's figures, the following reasons for the savings were identified:

- Active use of automation (schedules, ventilation automation)
- Safe handling of the smart home system (participants "feel safe" in the operation)
- Continuous use of the system
- High degree of energy awareness

It should also be noted that the savers did not show any changes in their living conditions over the duration of the study. This is another important indication of the impact of active use of the smart home system on savings.

Electricity consumption – Comparison with previous year consumption figures

64 households are available to compare the electricity consumption data of the reference year with the previous year's electricity consumption data. The frequency distribution of savings and additional consumption is examined. The participants are divided into different groups, see Figure 3. The relative proportion of study participants who saved electricity is 64%. In contrast, the share of participants who have increased consumption during the reference year is 36%.

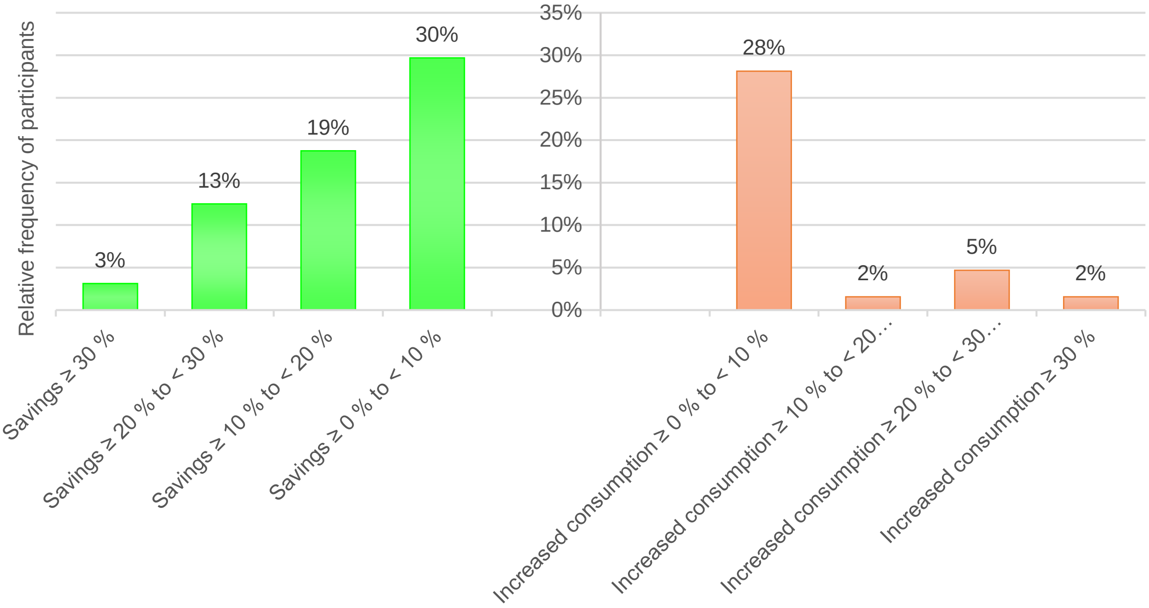

Figure 3. Frequency distribution electricity savings and increased consumption

The following Table 2 contains the most important consumption data regarding the consumption of electricity energy. On the one hand, it shows the total electricity energy consumption of all participants before and after the Smart Home installation and the difference between the periods. Furthermore, the minimum and maximum consumption of a participant is listed to show the range of the 64 usable consumption data (per household). In the column of absolute differences it is important to know that the differences for the minimum and maximum consumption are composed of the maximum saving and the additional consumption, these also reflect the results from Figure 3. As can be seen graphically in Figure 3, the data is a normal distribution. This also confirms the calculated standard deviation, since 95.45% of all measured values are found in the interval of the deviation +/- two σ sigma from the expected value, see Table 2 standard deviation.

Table 2. Electricity energy consumption before and after smart home and standard deviation

	Before Smart Home	After Smart Home	Difference absolute
All participants consumption	286.569 kWh	268.553 kWh	18.016 kWh (savings)
Mean per household (n = 64)	4.478 kWh	4.196 kWh	281 kWh
Minimum consumption	1.604 kWh	1.635 kWh	-1.906 kWh (additional consumption)
Maximum consumption	10.052 kWh	8.463 kWh	2.156 kWh (savings)
Standard deviation [δ]	1.575 kWh	1.459 kWh	719 kWh

Standard load profile vs. participant with the greatest energy savings. The relative saving of the selected household of the study compared to the average German household standard load profile [13] is about 0%. This means that the household is exactly the same as the German average in terms of the reference year. Since it is the participant who has achieved the greatest savings compared to previous years, this participant was significantly above the German average household before using the Smart Home System, see Table 2 maximum consumption. Figure 4 shows that active use of the Smart Home System has the potential to reduce electricity consumption sustainably. As a result, households with above-average electricity consumption can not only reduce it compared to previous years, but also come closer to or fall below the German average.

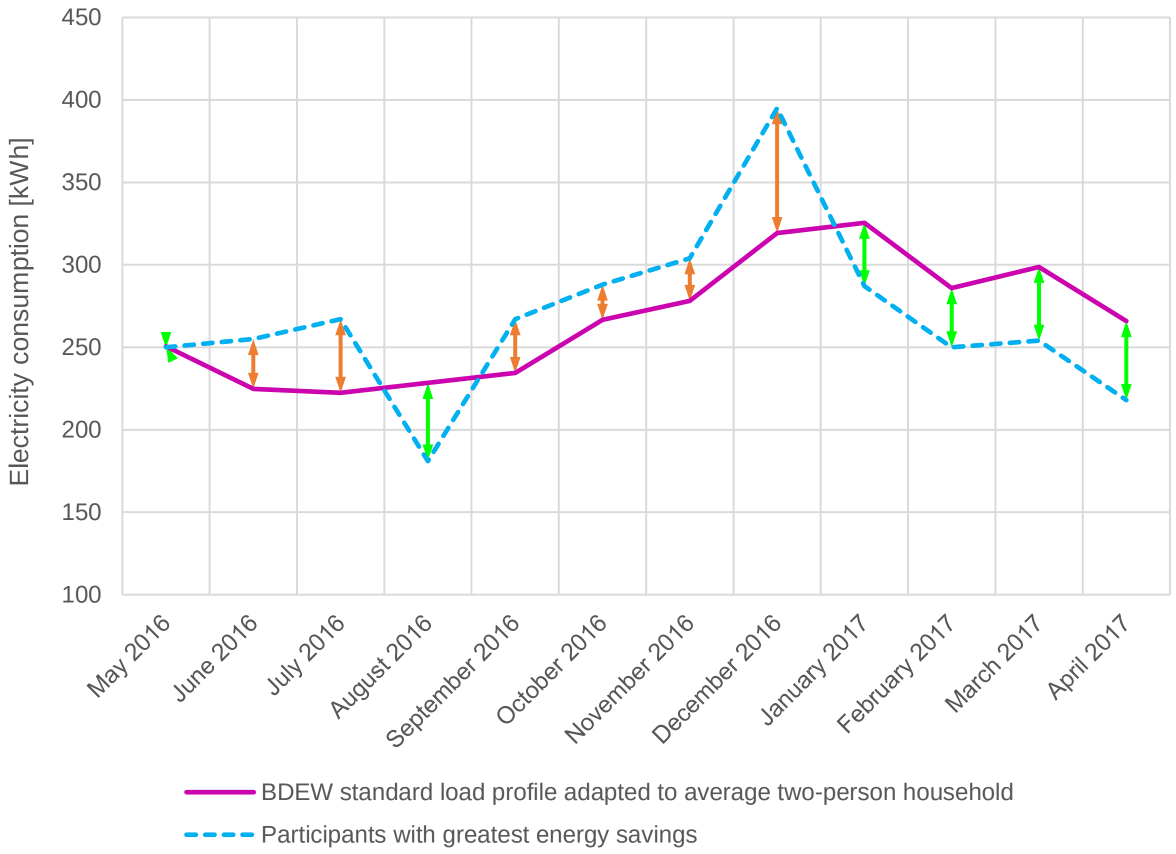

Figure 4. Comparison of the monthly consumption profile of the participant with the greatest energy savings

No correlation between household size and savings or excess consumption can be identified. For example, the households with the greatest savings are both one-person and four-person households. The situation is similar when considering age. The average age of the participants with the highest savings during the reference year is similar to the age of the participants with the highest excess consumption during the reference year. There is also no correlation between electricity savings and additional consumption and the gender of the study participants.

Comparison heating and electricity consumption

Finally, it is examined whether there is a correlation between electricity consumption and heating energy consumption. For this purpose, the results of the investigation of the heating energy consumption of a previous work are used. Based on both studies, 57 data are available for comparison.

The results of the investigation are shown in Table 3. Among the 22 participants who save both electricity and heating energy, six participants show similar savings behaviour. Furthermore, two participants who show high electricity savings also have high heating energy savings. Relative to the 22 participants who saved both electricity and heating energy, these results in a relative share of 36 %. This relative share is also obtained by looking at the 11 participants who showed an increase in consumption.

Table 3. Comparison of electricity and heating energy of the study participants

Savings and additional consumption area	Absolute number of participants	Relative number of participants
Saving electricity and heating energy	22	39%
Saving electricity	14	25%
Saving heating energy	10	18%
Additional consumption of electricity and heating energy	11	19%

Analyse Participant with the highest heating and electricity savings. By looking at a single participant, the potential of using a smart home system to save energy can be estimated. For this purpose, the monthly consumption profile of the participant with the highest potential for energy savings compared to the previous year's consumption is compared with the average consumption of German households in 2019. The participant with the greatest savings in both electricity and heating energy is taken into account.

Visualisation clustering data via k-means

Using cluster analysis (k-means), different data sets were compared with each other. The visualization by cluster analysis serves to reveal mathematical correlation of groups. As an example, the following data sets are compared with the heating energy consumption:

- Number of household inhabitants
- Living space (in m²)
- Index energy awareness (ranking 1 to 4)
- Readiness to recommend (through Net-Promoter-Score, ranking 1 to 10)

These exemplary data sets have an influence on energy consumption or are related to the use of the smart home system. Energy awareness is made up of a series of questions that were asked to the study participants via a survey, see chapter: *Data basis of the field-test*.

In order to perform the cluster analysis, the different data sets must first be z-transformed, as described in Chapter: *Measures of distance and similarity for metric variables (z-standardization)*.

In Figure 5 are the number of household inhabitants versus heating energy consumption. The blue cluster 1 shows especial a correlation between small numbers of inhabitants with low consumption. This imitates the dependence of the number of persons in the household and the heating energy consumption. Smart home systems can be used effectively with a small number of people in the household, due to shorter presence times and less space to heat.

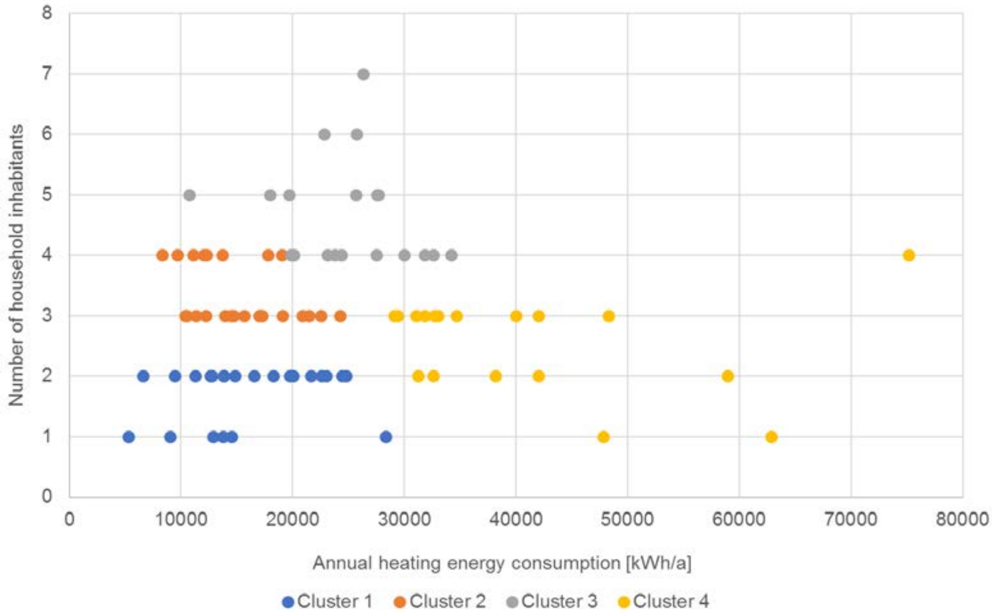

Figure 5. Clustering (k-means, z-standardization) heating consumption and number of household inhabitants

Figure 6 shows the living space versus heating energy consumption. As before, the blue cluster 1 also shows the area of small households, which also correspond to low consumption. No further conclusions can be drawn about the Smart Home System and the heated living space.

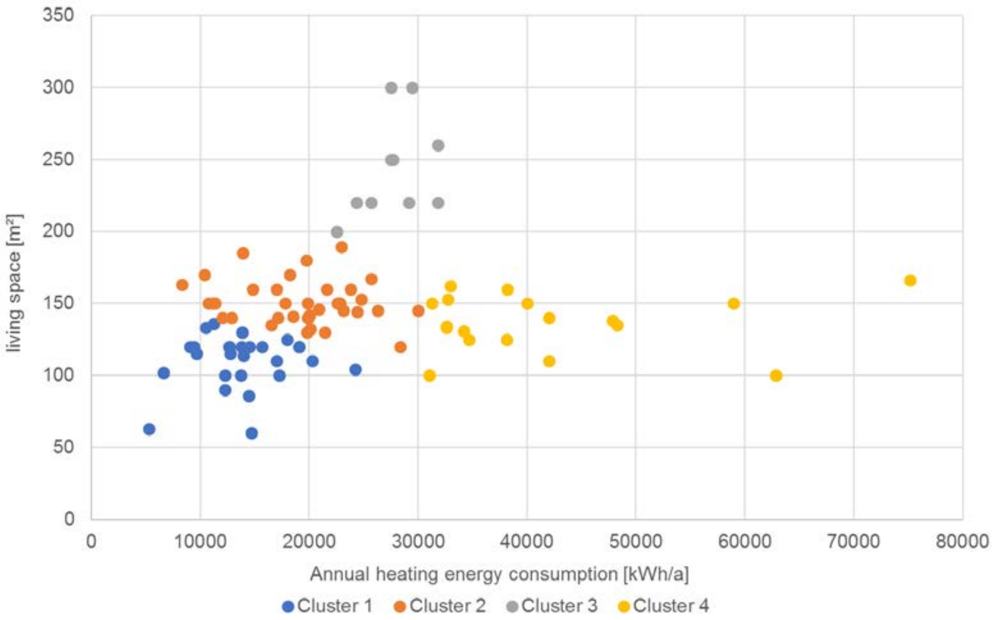

Figure 6. Clustering (k-means, z-standardization) heat consumption and living space

Figure 7 shows the energy awareness of the participants in relation to heating energy consumption. It should be mentioned that the higher the energy awareness the better it is rated (four corresponds a great energy awareness). In the diagram, it is noticeable that the blue cluster 1 corresponds to a great energy awareness and a low energy demand. Therefore, the thesis can be confirmed (see Chapter *Heating consumption*) that people with a high degree of energy awareness can save a lot of energy by using the Smart Home System.

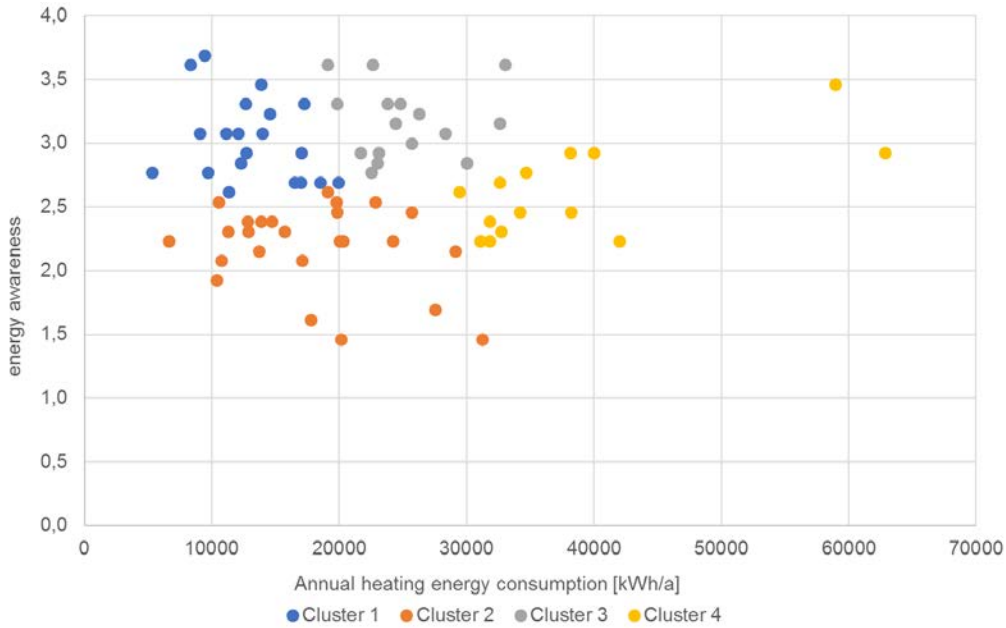

Figure 7. Clustering (k-means, z-standardization) heat consumption and energy awareness

Figure 8 shows the willingness to recommend the smart home (Net-Promoter-Score) compared to heating energy consumption. It should be noted that ten stands for a high and one for a low willingness to recommend the smart home system. The evaluation shows that clusters 1 (blue) and 3 (grey) each have high willingness to recommend smart home. This also reflects the results from Chapter *Heating consumption* (rebound effects). The fact that participants with increased consumption by the Smart Home System heat more, as the radiators are easier to control and make the user feel more comfortable.

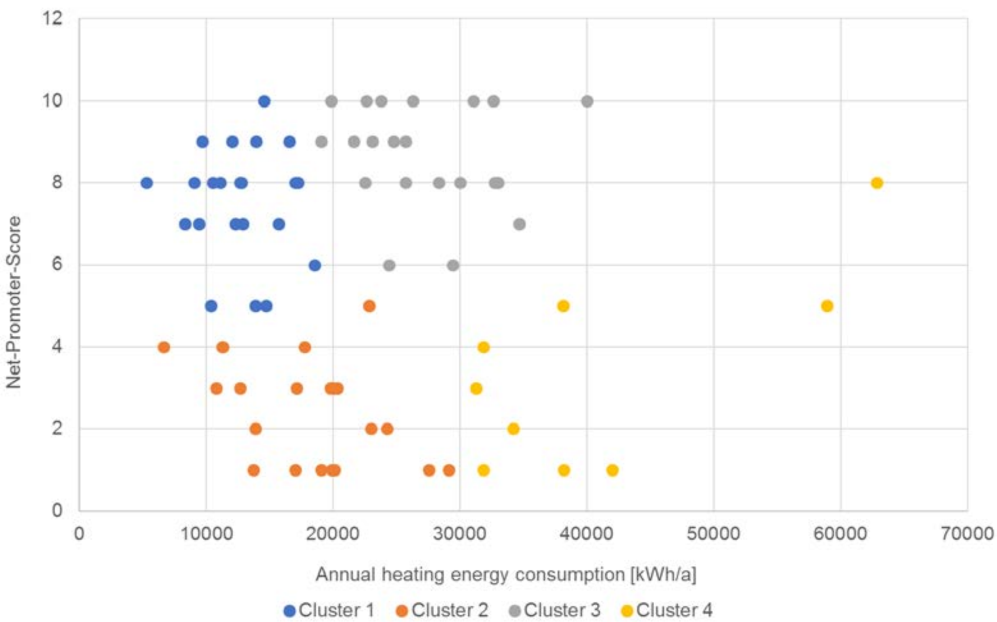

Figure 8. Clustering (k-means, z-standardization) heat consumption and Net-Promoter-Score

DISCUSSION

The evaluation of the heating and electricity consumption could be evaluated by comparing the previous years with the reference year. In the case of the changes in heating energy consumption due to the use of the smart home system, it is noticeable that a major influencing factor is user behaviour, as the rebound effects have shown. Although the spread in heating energy consumption is based on an increase in consumption of 25.5% and savings of up to 33.3%, it should be noted that an average saving of 4% was achieved. This is similar to the results of the study [5], which investigated the use of smart thermostats.

The electricity consumption does not show any particular correlation with other influencing factors and corresponds to a typical spread. It should also be mentioned here that a correlation with the standard load profiles was also carried out, but since the deviation was small, this section was neglected in the paper.

When comparing heating and electricity consumption, the participant with the highest heating and electricity savings turned out that user behaviour is an important criterion for saving energy. This participant also has a high energy awareness rating.

Visualisation using cluster analysis (k-means) enabled the energy data to be compared with hard data and soft data. However, in order to obtain more precise information on the behaviour of the energy demand, a higher-resolution database is required. Monthly consumption values provide only a first estimate, these should be replaced for example by 15-minute values. This would also make it much easier to identify a direct influence of the smart home system.

CONCLUSION

In the context of this paper, the existing data sets from the smart home field-test "Smart Home Rösrath" were further analysed. Besides the evaluation of the consumption data (electricity and heat), the focus was on establishing a correlation between the socio-demographic data. In this socio-technical analysis, it was possible to summarize energy awareness in an index evaluation using survey data sets on user behaviour. This made a correlation possible using the consumption data. Data sciences and analytics methods were used for the correlation, such as the k-means method, which, through the Z-transformation, made it possible to compare two different parameters. Dependencies of the energy consumption and different influencing factors by the user behaviour could be proven. These methods are especially suitable for future Big Data applications, therefore it is recommended to use a higher measurement interval for future investigations of energy demand behaviour.

The empirical investigation has shown in field-tests that high savings of over 30% for electricity and heat are possible. Support by the smart home System could be proven but an even greater influence by the user behaviour of the participants. On the other hand, a high additional consumption of the participants was also found, at this point in the future the smart home System can also be used to provide information and avoid additional consumption.

Within the framework of this paper, it has been possible to determine the energy demand behaviour with the help of a socio-technical analysis. This provides the basis for future studies to test new smart technologies or business models in the household sector with the inhabitants. The right interaction and acceptance of smart technologies with the user goes hand in hand with saving energy.

ACKNOWLEDGMENT

The authors thanks and acknowledge the support of the European Union's Seventh Framework Program for research, technological development and demonstration under grant agreement no 314441.

Further the authors thanks and acknowledgethe support of the Ministry of Economics, Innovation, Digitalisation and Energy (MWIDE) of North Rhine-Westphalia (DE) and of the European Regional Development Fund (ERDF) funding no 0600037.

REFERENCES

1. Bundesministerium für Umwelt, Naturschutz und nukleare Sicherheit (BMU), Ed., "Klimaschutzplan 2050: Klimaschutzpolitische Grundsätze und Ziele der Bundesregierung," 2016.
2. Bundesministerium für Wirtschaft und Energie (BMWi), Ed., "Energieeffizienz in Zahlen: Entwicklungen und Trends in Deutschland 2018," 2018.
3. Prof. Dr. Viktor Grinewitschus, David Reiners, Andre Beblek, Grundlagenstudie: Smart Readiness Indicator (SRI). [Online]. Available: https://issuu.com/pinx-design/docs/10_sri_issu
4. A.J. Bernheim Brush, Bongshin Lee, Ratul Mahajan, Sharad Agarwal, Stefan Saroiu, Colin Dixon, University of Washington, "Home Automation in the Wild: Challenges and Opportunities: SIGCHI Conference on Human Factors in Computing Systems," 2011.
5. D. Schäuble, A. Marian, and L. Cremonese, "Conditions for a cost-effective application of smart thermostat systems in residential buildings," Applied Energy, vol. 262, p. 114526, 2020, doi: 10.1016/j.apenergy.2020.114526.
6. Fraunhofer-Institut für Bauphysik IBP, Simulationsstudie zum Energieeinsparpotential einer Heizungsregelung mit Abwesenheitserkennung und Wetterprognosen.
7. T. Schneiders, T. Rehm, L. Hilger, and C. Kleinschmidt, "Smart Home Field Test - Households: Combined Efficiency Large Scale Integrated Urban Systems," University of Applied Sciences Cologne (TH Köln), 2018.
8. Frederick F. Reichheld, "The One Number You Need to Grow," 2014.
9. Plattform „Innovative Digitalisierung der Wirtschaft" im Nationalen IT-Gipfel, Fokusgruppe Intelligente Vernetzung / Projektgruppe Smart Data, Ed., "Smart Data in der Energiewirtschaft," 2015.
10. J. W. Foreman and J. Schmidt, Smart Data statt Big Data: Wie Sie mit Excel-Analysen das Beste aus Ihren Kundendaten herausholen, 1st ed. Hoboken: Wiley, 2015.
11. P. P. Stein and S. Vollnhals, "Grundlagen clusteranalytischer Verfahren," Working Paper, Institut für Soziologie, Universität Duisburg-Essen, Duisburg, 2011. Accessed: Mar. 9 2020
12. J. Bortz and R. Weber, Statistik für Human- und Sozialwissenschaftler: Mit 242 Tabellen, 6th ed. Heidelberg: Springer Medizin, 2005.
13. BDEW Bundesverband der Energie- und Wasserwirtschaft e.V., *Standardlastprofile Strom.* [Online]. Available: https://www.bdew.de/energie/standardlastprofile-strom/