Home Automation for a sustainable living – Modelling a detached house in Northern Finland

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Abstract

This paper presents a model of a detached house in which home automation has been progressively introduced into the building. The model integrates different factors related to end-user behaviour and decision-making regarding the management of electrical energy consumption, and integrates a gradual end-user response to home automation measures. The presented model aims to show the potential economic benefits obtained by the modelled changes of end-users' behaviours within a smart energy network based energy system. Matlab/Simulink is used as a simulation tool for representing the model in which a 10 year database of Nordic climatic data has been built in, on an hourly and half hourly basis. The modelled building environment comprises twenty-one appliances and two lighting systems with different power rates. Each appliance and light bulb is individually measured. The feedback methods assessed were self-comparison, inter-comparison, and a target based system. The effect of home automation on energy consumption at the building level is assessed, and the importance of end-users in energy reduction is highlighted. The model categorises "green" and "brown" energy users and integrates their behavioural profiles within the end-user response. As part of a smarter electricity management system, the home automation system is able to interact with other buildings, either in terms of geographic or building infrastructure similarities. This will enable taking or modifying decisions at any given time, thus contributing to the local flattening of power demand. Such systems must work hand-in-hand with the grid operator.

1. Introduction

With the massive deployment of smart meters across Europe allowing digital measurements, energy companies and Public Institutions have access to a consequent database of energy consumption data throughout a country. European Union (EU) Member States have the obligation of implementing smart meters covering 80 % of consumers by 2020 at the latest [1]. In contrast to European Directive 2012/27/EU [1], Finnish legislation (18.1.2013/50) sets a deadline of 2014. The deployment of smart meters also brings up the issue of data security and use of the collected information, in particular in relation to the role of energy utilities and Public Institutions [2]. Legal obligations to increase energy efficiency also provide a motivation to the deployment of renewable energy sources, as a vector for energy production, and an increase in the energy efficiency of buildings. Home energy management can have a significant role in contributing to energy efficiency and cutting down peak load. This can be achieved through an active collaboration of energy consuming systems and the information network e.g. at the local level [3], [4]. Putting together the different factors mentioned involves the development of a smart energy network (SEN), capable of managing the energy system through constant monitoring.

SEN can be seen as a multi-layered configuration of the energy infrastructure, within which smart buildings are at its foundation [5]. Within a SEN architecture, the energy network is split into multiple complexes, forming a set of networks that communicate between each other [6]. Each horizontal area belongs to the same layer and vertical area to different layers. Energy and data may travel horizontally and vertically but not in diagonal. The main objective in this context lays in an increase of energy efficiency along with an economically viable reduction of environmental impacts where home automation has an important role. The effect of energy efficiency on the decrease of energy consumption at the local level is often offset by the rebound effect. The direct rebound effect, which is affected by the variation of the home energy budget, shares a responsibility in the success of energy efficiency measures [7]. Analyses of energy end-use at the home level become necessary for structuring a bottom-up system.

For the past fifteen years, surveys of energy consumption habits have been carried out across European households. Most of the surveys were looking at the effect of energy feedback to end-users' behaviour ([8-11]). Earlier work [6] showed that retrieving feedback regarding end-users' energy consumption could affect positively the overall impact on energy efficiency. An average decrease from 4 to 20 % of energy consumption has been found in the literature [12].

Modelling daily energy demand has been tackled from different angles in a top-down and bottom-up approach. A non-exhaustive list of these models have been described in [13] showing details of the different ways for representing the energy consumption in households. The timescale represented in previous models goes from hours to minutes [14-16]. In order to have a detailed energy profile, the bottom-up approach appears to be the most suitable method, compared to a top-down approach, where the overall energy consumption is broken down to individual appliances [16]. Modelling the energy consumption profile generally uses measured data from field tests as input data [13], [17]. Depending on the method used, energy consumption may be simulated from a human perspective by creating occupancy scenarios that will enhance the use of appliances. Grandjean et al. [13] pointed out the difficulties of such a technique, as it requires an extensive database on human behaviour and the activities undertaken. It is preferable to find a solution via the pattern of appliances' usage and deduce from it the human activity within the household. A comparable approach has been carried by Borg and Kelly [18] for evaluating the impact of appliances on energy efficiency in the future. They have not considered either the probability of an event or action occurring in the eventuality that home automation through smart metering would be applied in dwellings.

Modelling an energy system from the bottom up, more appropriately takes into account distributed energy systems [19] as an alternative to centralized energy production systems. Such energy architecture is being developed in parallel with the development of micro- and small-scale energy production systems [20]. Currently, Finland is considered to be a centralized system but has a considerable potential for having a decentralized system.

This paper investigates a bottom-up approach model centred on the use of appliances. The first part highlights the model description and its architecture. The second part details the data collection involved in order to run the model. The third part illustrates the model with the results obtained. Validation of the model puts in perspective the obtained results with real time energy consumption data of typical Finnish detached houses from the Oulu region.

2. Model

Structuring a model with a bottom-up approach requires detailed information regarding the studied living environment. Stokes [21] introduced a widely used system taking into account specific information related to the appliances, the socioeconomic status of the occupants, and a large panel of measured data as the basis for a statistical analysis of the energy profile. The energy system built with the bottom-up approach thus requires a precise, pre-defined system that creates a consequent database.

The model presented in this paper is based on an hourly scenario of appliance and lighting use. Based on a pre-selected number of users, their housing types, and the corresponding number of rooms, the model describes the usage of twenty-one pre-defined appliances. The lighting system presents two technological alternatives (incandescent and low consumption bulbs) in order to describe the energy consumption related to a lighting system. The model associates pre-determined energy consumption with the usage of different appliances (Figure 1). This is based on the assumption that, in order to use some of the appliances, a given number of persons are expected to be in the house, therefore consuming a statistically pre-defined amount of energy.

The user behaviour is evaluated depending on the feedback strategy chosen for the simulation. Feedbacks are dependent on the controller side of the model, which is used as a statistical tool. In this model, feedbacks are based on the self-consumption, the inter-comparison and the target based system.

The controller allows the piloting of certain appliances that are flexible over time, such as the washing machine and the dishwasher. The controller crosschecks information with the grid and between appliances in order to electrically decrease the power demand of relevant appliances during peak load hours.

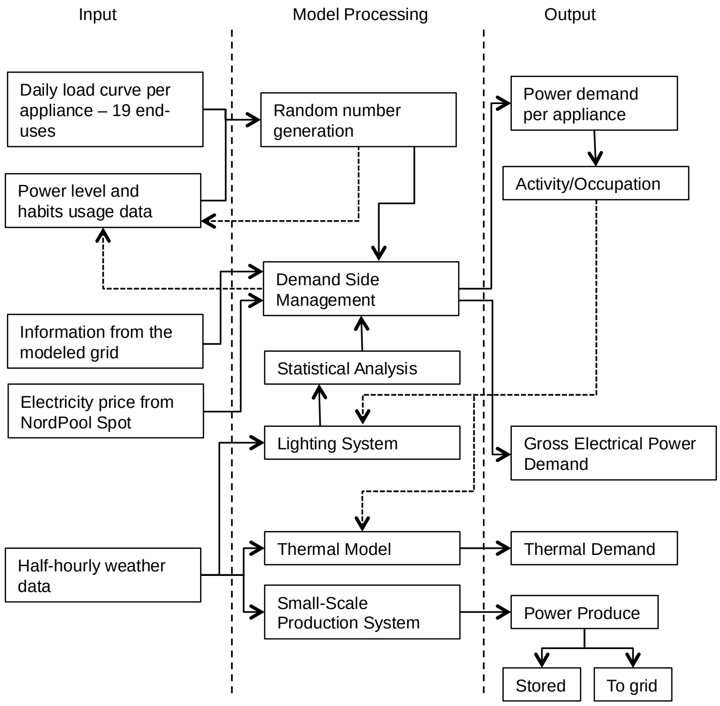


Figure 1. Block diagram of the model developed (based on [13])

2.1 Scenario Architecture

The model is built on an hourly basis using statistical results from earlier research [6].Firstly, the user behaviour regarding the use of appliances follows results coming from the Energy-using Product (EuP) [17] surveys on energy efficiency and use. These large-scale surveys intended to pattern the use of appliances in order to settle the energy efficiency rating scale under the European Energy Efficiency Directive. An example of data that can be extracted from these studies is shown in Table 1 which shows the different number of washing machine cycles that occur during the week per inhabitant. In the case of a washing machine, the type of program as well as the mean time for carrying out the action is given. Other information such as the average energy use per year or information that belong to specific appliances (e.g. mean recharging time of a mobile phone) is provided. These data set the model boundaries.

Table 1. Time of use and probability of activity occurrence for a washing machine

	Nbr of wash/week
1 person	2.1
2 persons	3.4
3 persons	4.9
4 persons	6.4
5 persons	6.3
6 persons	7.0

Temperature	Distribution	Time [min]
Cold	02 %	35
30°C	09 %	40
40°C	49 %	45
50°C	07 %	50
60°C	27 %	60
90°C	06 %	70

The second part of the model consists of tracking the daily energy profile of each appliance. In order to understand how an appliance is used, results from the REDMODECE [3] European Project have been processed to give mean daily energy profiles for the twenty-one appliances used in this model. To create these vectors, empirical values from multiple surveyed houses have been extracted from comparable Nordic countries (Norway and Denmark). In addition, it seemed relevant to integrate in the model the use of a sauna, considering that, in Finland, there is an average of 0.38 electric sauna stoves per capita [22]. Therefore, field data and/or assumptions for sauna stove use were added.

Figure 2 indicates the daily usage of the abovementioned electric appliances. Each plot represents the probability function for an appliance to be used over the course of a day. This explains the very high occurrence for some appliances such as a hair dryer in certain periods, due to the low probability of use another time of the day. Note that the hairdryer and iron peak at 56 % and 33 % respectively.

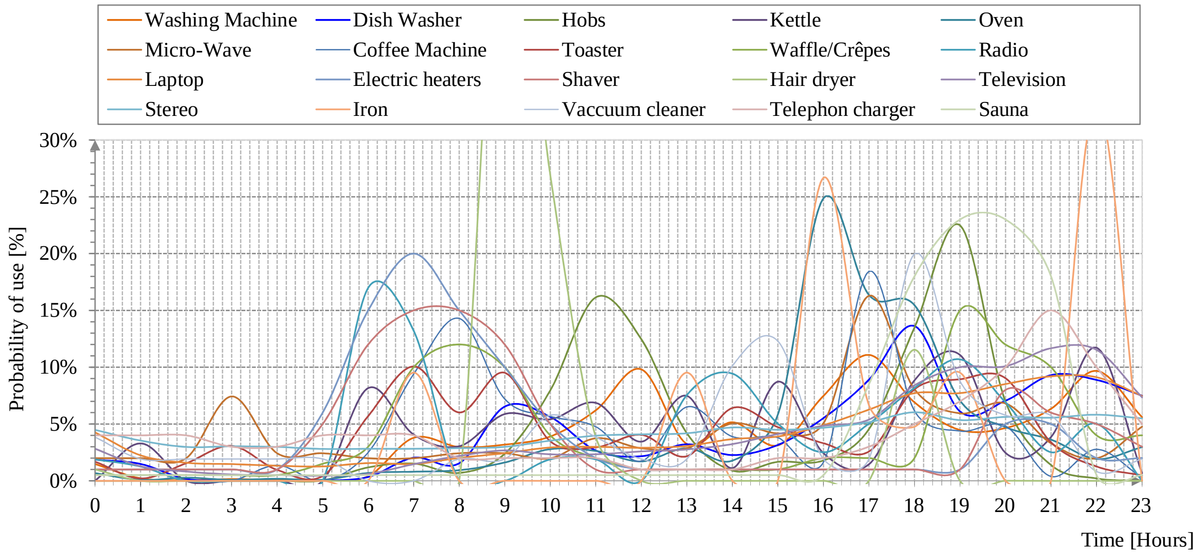


Figure 2. Daily energy profile for twenty-one appliances extracted from electric measurement

Once the profiles have been drawn out, daily and weekly safeguards are defined limiting the usage of an appliance [6]. Equations (1-4) express the conditions to be verified in order to have a confirmed action at t = n.

$$\bar{A}_{d-1} < \frac{2}{7} A_{w-max} \tag{1}$$

$$\text{and } \bar{A}_{w-1} < 1.1 A_{w-max} \tag{2}$$

$$\text{and } C_{h\,n} < R_h \sim U(0,1) < C_{h\,n+1} \tag{3}$$

$$\text{and } R_d \sim U(0,1) < C_w \tag{4}$$

Where $\bar{A}_{d-1}$ is the mean activity of the previous day, $\bar{A}_{w-1}$ is the mean activity of the previous week, A_{w-max} is the maximum weekly activity as defined in Table 1, C_{hn} is the probability of use at t = n and $C_{h\,n+1}$ is the probability of use at t = n+1, C_w is the probability that an action will occur over the week or the weekend, $R_h \sim U(0,1)$ and $R_d \sim U(0,1)$ are uniform random numbers generated for the hourly and daily activities respectively.

The usage model of appliances allows the occupation within the detached house to be defined, which is also used for the lighting model. The available luminosity is calculated following solar irradiation. The relationship between solar irradiation and luminosity has been empirically established by Yokoya and Shimizu [23]. The lighting model is built using three components; namely the activity/occupation scenario, the available natural luminosity, and the luminosity required to carry out a certain task. Combining these three factors establishes the probability of use of light between 10% and 100%, where 10% is the probability of using artificial light on a very clear day and 100% is the probability of using light when the natural light is non-existent.

2.2 Demand Side Management

Including the user response within the model required the use of a demand side management (DSM) model. Consumption data are used for statistical purposes, monitoring the average appliance usage with reference values [17] on daily, weekly, monthly, and yearly levels.

These average consumption data are used for self-comparison and giving information to the end-users if they have over-consumed compared to the four reference levels. Independently from the user type, the fact that the end-user does not reach the level of consumption from the previous reference period (weekday, week, month or year) increases the acceptance of consuming energy at t = n [6].

The target-based system uses the previous data to build up the target for each dwelling (in case of multiple dwelling in the simulation). The tolerance for energy consumption increases or decreases depending on how well the end-user has performed at each iteration.

For both the self-comparison and the target-based system, the user response follows three trends, depending on the nature of response to the advice coming from the DSM system. A “green” user is considered to have a high positive response to the advice due to his/her personal background. In this context, such user is considered to have a standard positive response of 70 %. Similarly, an “orange” user will have a 50 % positive response, and a “brown” user a 30 % positive response. It is considered that a user would not have a 100 % positive response to any of the advice coming from the DSM system. The DSM ponders the standard response. Depending on the electrical consumption and the advice that the DSM may give, the standard response varies by up to +10 %. The user response will affect three variables related to use of the appliances: reducing the time of use of an appliance by integrating low-cost energy efficiency measures i.e. e.g. covering the pot, reducing the use of light; shifting the use of an appliance to an alternative time in case of peak load hours e.g. the use of the dishwasher during the night. In this case, the shifting requires the consent of the end-user but the time of the action is controlled by the automation system; and shifting the use of the sauna up to 1 hour in case of peak load. In the case of shifting the sauna use, the agreement of the end-user on actually agreeing on offsetting the use of the sauna from the traditional hour to another one is required. Therefore, it has been assumed that the end-users will not agree on taking a sauna in the middle of the night but would rather change the traditional sauna time by 30 minutes up to 1 hour.

The control system integrated in the model is capable of automatically postponing an action for specific appliances such as the washing machine or the dishwasher to any given time. It is highly unlikely that a control system would ever automate the use of all appliances in a household, thus a restriction to these two appliances has been made. Furthermore, in case of peak load time detected on the grid, the household control system is capable of reducing the power demand of appliances that require high power e.g. kettle, and iron. In these ways, the household power demand is reduced and a decrease in the peak load at the grid level is expected. Decision-making by the control system is currently based on the price information that it is receiving from the grid. In the case of a fixed-price system, critical hours are perceived during the high price period. In case of real-time pricing based on the electric spot price system, a combination of the real-time pricing and the price forecast is made in order to define the peak load time and thus apply a reduced power demand from the appliances.

3. Data collection

Running the model requires the use of reliable data, including the price of electricity on the energy market, the power levels for each appliance that defines the quality and the age of the appliances, and the weather conditions on a regular basis. Each dataset was combined together into two monotonic increasing vectors of half an hour and an hour.

3.1 Climatic Data

In order to create a dynamic model, data on temperature, solar irradiation, wind speed, wind direction, relative humidity, sky condition, atmospheric pressure, wind chill, dew point temperature and visibility were retrieved from an online weather database [24]. Raw data were given for 30 minutes samples on average, meaning that data processing was a necessary step to have a uniform vector of data. The Finnish Meteorological Institute issued the global horizontal irradiation data on an hourly basis for the years 2004 to 2012.

For the years 2000 to 2002, large amounts of data were found to be missing. In these few cases, artificial data was calculated from the mean variation of a variable for the previous and the following year, with the reference value of the previous hour. In the case of most recent years, smaller amounts of data were found missing for up to 6 hours in a row. In this case, a linear interpolation between the two existing values was created. The full processed dataset can be found in [6].

3.2 Appliances Data

The power demand required for each appliance was defined following the Best Available Technology (BAT) defined in the EuP research tasks [17]. As long as the information was given in terms of kWh per year, the total working hours per year for each appliance were taken. The ratio between the total energy consumption per year and the total number of working hours gave an average power demand in expressed in kW. Furthermore, seven categories (from A to G) were defined in the EuP report, “A” being the most efficient appliances and “G” the least efficient appliances. In order to select a certain category of appliance to be implemented within the model, each appliance was divided into three categories: A/B, C/D, and E/F. Each category was assigned a median value of the power demand calculated using the previous method as summarised in Table 2.

Table 2. Rated power for each appliance used in the simulation

		Based on the European Energy Label			
House zone	**Appliance**	**A/B Category [kW]**	**C/D Category [kW]**	**E/F Category [kW]**	**Standby power [kW]**
Kitchen	Washing machine	0.306	0.410	0.520	N/A
	Dish Washer	0.929	1.250	1.600	N/A
	Electric Cooktop		4.000		N/A
	Kettle	2.000	3.000	4.000	N/A
	Electric Oven	4.000	5.000	6.000	0.005
	Micro-wave	0.950	1.200	1.400	0.005
	Coffee Machine	0.600	0.800	1.000	N/A
	Toaster	0.800	1.300	1.600	N/A
	Waffle/Crêpes	0.900	1.200	1.500	N/A
	Fridge	0.300	0.400	0.600	N/A
Bedroom	Radio	0.005	0.008	0.010	0.001
	Laptop Active	0.060	0.080	0.120	N/A
	Laptop Sleeping	0.003	0.005	0.010	N/A
	Laptop off mode	0.002	0.003	0.006	N/A
	Telephone charger	0.010	0.015	0.020	N/A
Bathroom	Electric heaters		1.500		N/A
	Shaver	0.010	0.015	0.020	N/A
	Hair dryer	1.000	1.200	1.500	N/A
	Sauna stove		6.000		N/A
Living Room	Television	0.125	0.150	0.200	0.005
	Stereo/Hi-Fi	0.080	0.100	0.120	0.001
Cleaning Tools	Iron	1.000	1.300	1.500	N/A
	Vacuum cleaner	0.700	1.200	1.400	N/A

3.3 Electricity price data

In order to integrate the price variation of electricity in the model, the public prices from the main energy retailer from the Finnish Oulu region (Oulun Energia Oy) have been compiled. Three contracts, offered from the same company, have been included. Each contract allows the end-user to choose what type of energy production system their energy comes from i.e. biofuel, wind energy or mixed energy. A fourth option was given to the end-user by selecting the real-time pricing system. A more complex system could be built in order to take into account the variation of energy demand on the network [25]. In this model, a method for creating the real-time pricing based on historical data has been developed. This approach requires the hourly price of electricity on the spot price market on one hand, and the average retailed electricity price to the end-user for the same period on the other hand. Both datasets are publicly available from the Energy Market Authority [26]. Using Equation (5) allowed the establishment of an hourly purchasing price for the end-user by correcting the spot price from its extreme incentive values, which can reach thousands of €/MWh on the positive side for some specific hours in order to increase energy production, and may be a negative price to reduce energy production.

$$P_h = \overline{P}_m \times \frac{P_{h-\mathrm{Network}}}{\overline{P}_{m-\mathrm{Network}}} \qquad (5)$$

Where P_h is the hourly price of electricity for the modelled dwelling [€cent/kWh], $\overline{P}_m$ is the monthly average price of electricity for dwelling [€cent/kWh], $P_{h\text{-}Network}$ is the hourly electricity price on the spot price market [€/MWh], and $\overline{P}_{m\text{-}Network}$ is the monthly average price of electricity on the spot price market [€/MWh].

4. Results and Discussion

The model presented above aimed to draw daily energy demand profiles coming from the appliances plus lighting systems. Moreover, the implementation of home automation is included in the model with the aim of increasing the effectiveness and efficiency of the household's energy consumption.

The model used measured data in order to build up the scenario of energy demand. The modelled data were contrasted with real-time energy consumption measurements carried out in 16 households in the Oulu region in 2012 [27]. The mean daily energy demand profiles have been drawn for the entire year in the case of the modelled dwellings and a typical four-person family house in Oulu (Figure 3). General electricity consumption as well as the electricity price was taken every six seconds for each phase (in the case of three-phase houses). These houses had dynamic pricing following the spot price market. The electricity consumption recorded varied from 5 929 kWh/y up to 13 706 kWh/y for the period of January 2012 to January 2013. The mean daily energy profiles aim to recognize a tendency in the energy production for each dwelling. A common pattern in a Finnish home sees a peak of consumption in the evening due to the use of the sauna stove, which levels out the other peaks occurring during the day e.g. the morning peak.

The modelled house was set for the twenty-one appliances named earlier and all of the appliances were classified as being A/B labelled. As an indicator, the sauna stove used for the modelled house was set to 6 kW as mentioned in Table 2. The overall electricity consumption coming from the appliances has been found to be around 4 501 kWh/y which is correlated with the findings in the European ODYSSEE MURE project and by the Sähkötohtori Analysis [28]. The measured data were carried out in a four-family detached house (in Oulu, Finland), which is equipped with a 10 kW sauna stove.

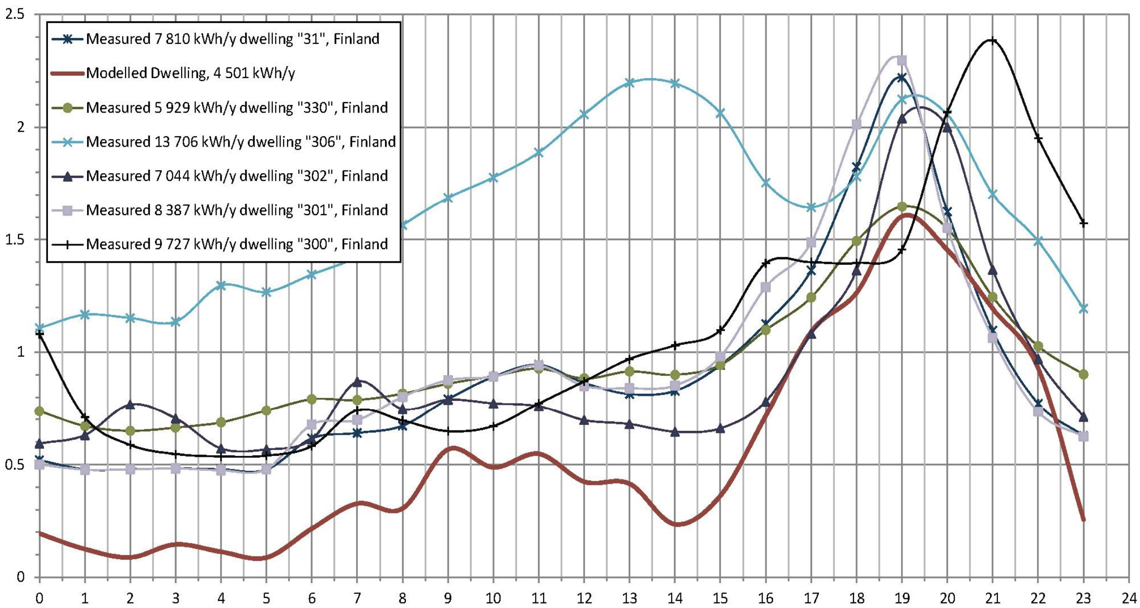
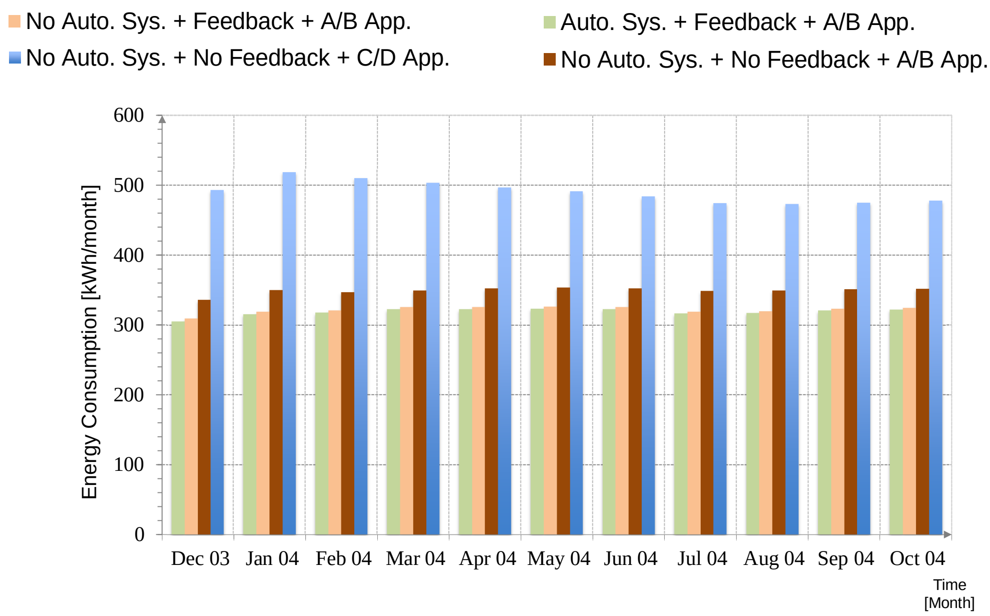


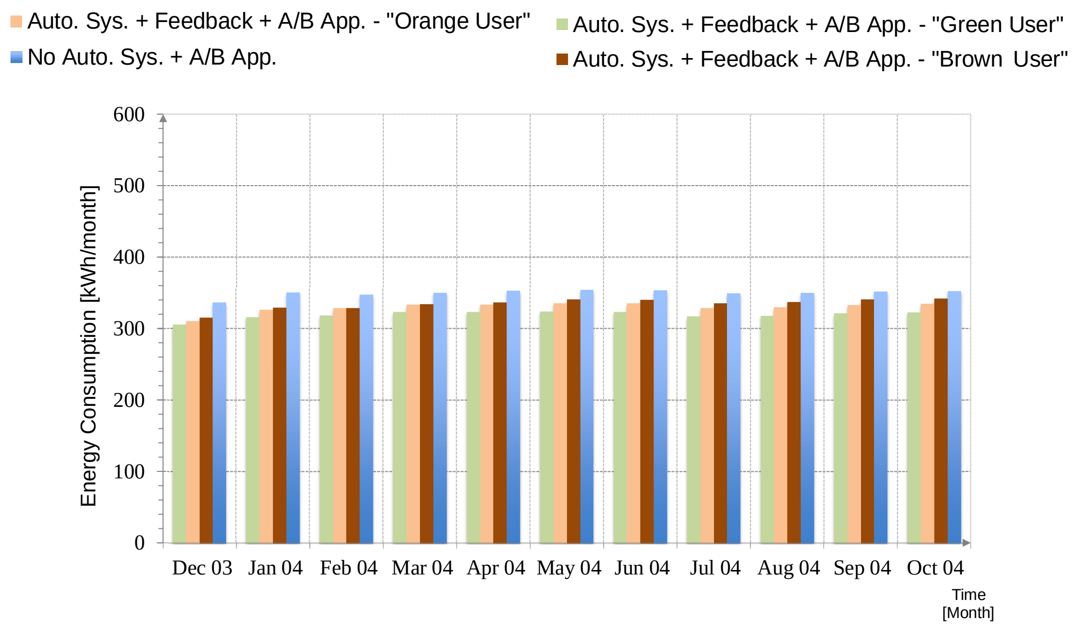
Figure 3. Comparison of a dwelling modelled with real time data measured in a four-person detached house in Oulu, Finland

It is not yet clear how the offset (of approximately 400 W of average power demand) shown in Figure 3 appeared. Our assumption is that it could be an electric under-floor heating in wet rooms, as is common in Finnish homes. This would be on constantly during certain periods of the year and it was not included in our model of the detached house. Earlier research has shown [6], [28] that the share of electricity demand for a secondary heating system may be considered as the highest proportion of electricity demand, reaching up to 50 % of electricity consumption of detached houses in Finland. Nevertheless, it can be pointed out that the trend of modelled mean power demand follows the trend of data collected in real houses, giving confidence in the model.

We focused on the change in energy consumption due to the introduction of energy efficient appliances (Figure 4 a.), and on the impact of user response on final electricity consumption (Figure 4 b.). The simulation showed a decrease in energy consumption of 30% using the same scenarios when all C/D labelled appliances were replaced by A/B labelled appliances. In the second stage, a feedback system was introduced in the model in order to simulate the effect of providing data information to people using self-comparison or a target based system. The simulation presented a decrease of the overall electricity consumption by 8 %, which is coherent with the findings from Ehrhard-Martinez [12]. In the last stage, the automation system allowing the direct control on the washing appliances managed to decrease the energy consumption by 1 %.



a.



b.

Figure 4. a. Consumption level by upgrading the technology installed in the dwelling, b. Monthly energy consumption level by user category.

Figure 4 b. indicates the importance of user response on energy consumption. The difference of decrease in energy consumption between the two extreme categories varies from 3.3 % up to 7 % depending on the month. Compared to the base scenario where no feedback system is installed within the home (the brown bar on Figure 4 a. and the blue bar on Figure 4 b.), the difference in electricity consumption between the base scenario and the scenario that considers a high positive response from the end-user may reach as high as 10.9 %.

In the context of flattening the daily energy demand profile, the model looked at the consequences of consumer feedback and home automation on the mean daily electric demand. The shifting of electricity from one particular hour to another one can be seen in Figure 5. On one hand, the electric consumption from 12am to 6am increased by 50 %. On the other hand, the electric demand from 7am to 12pm slightly shifted down from their original level. This longer period of negative shift supports the decrease of energy consumption over the day. This is explained by the feedback effect that influences the way appliances are used and offers up to 10 % reduction of energy consumption, compared to the original demand profile.

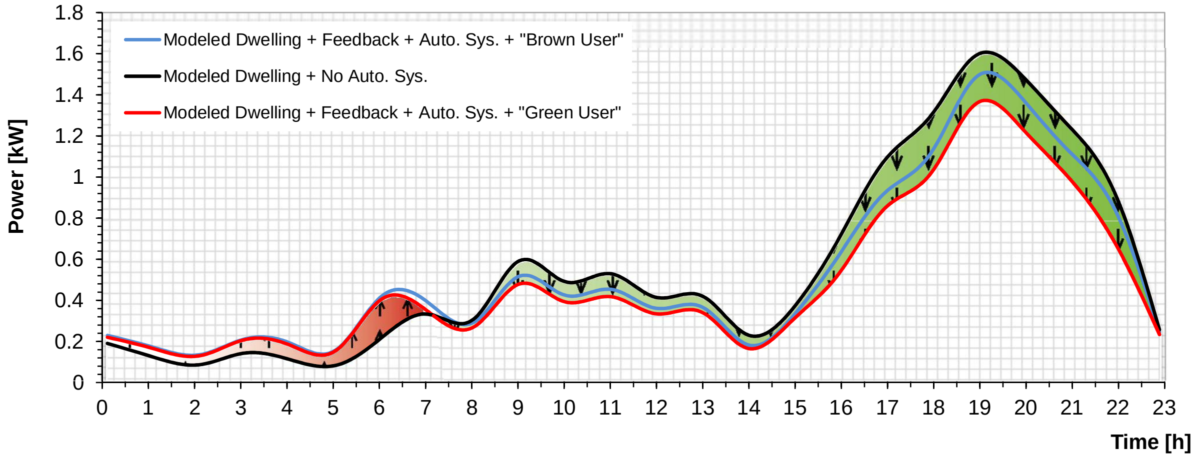


Figure 5. Effect of feedback strategies on demand profile and home automation in a detached house

The shift of energy demand seen in Figure 5 has to be balanced between the shift due to the automatic controller, and the one due to human behaviour. The latter is directly linked to user response and the way that end-users are utilizing their appliances at home. Thus, the “Brown User”, with its lower response and more frequent use of certain appliances may have a higher consumption than an end-user with a higher positive response when the system is asking to reduce the demand (see the Blue plot and the Red plot between 5 and 6 in the morning on Figure 5).

5. Conclusions, Recommendations and Future work

In this paper, a model of daily energy demand in a detached house in Finland has been set out. The model showed concordance with real data measured in a Finnish household. The model also integrated three types of user-responses as well as home automation, in order to control the use of programmable appliances. In terms of feedback impact, the model showed similar results to those found in the literature i.e. an average reduction of household electrical consumption by 8%. The automation system controlling the dishwasher and washing machine was able to decrease overall energy consumption by 1 %. In order to flatten the mean daily electricity consumption profile, some peak loads were shifted from the evening to the night period.

In order to fully use this model, it should be combined with a layered-grid model in charge of the energy management of multiple micro-grids. Such architecture should support a bottom-up approach of the electric infrastructure for creating dynamic pricing and managing the energy by geographical sectors. This model represents a starting point for evaluating the possibility to switch the mostly centralized energy system to a hybrid, mostly decentralized energy system. In this sense, the limitation of the model presented in this paper challenges to build up of viable scenarios involving dynamic pricing that would take into account the energy demand for building in the same geographical area.

Further work needs to be done in order to improve the model and get a better profile for each dwelling. Development should firstly focus on a minute-based electricity demand simulation, assuming that the output function would still be flexible enough to simulate a meter communicating hourly or daily data to the grid. Linked to the model, the daily energy demand profile per appliance will be varying in time, meaning that each appliance will follow the pre-defined energy profile and will evolve with the simulation time in order to integrate the end-user response and its effort for shifting the use of appliances in time. For integrating each aspect of energy efficiency, the direct- and micro- rebound effect should be integrated for each appliance and for the household. Finally, defining the appliances present in the households should depend on the end-user's definition within which appliances may be recurrent e.g. multiple TVs, video games and so on. In the future, the model should assess the impact of real-time pricing (hour-to-hour or minute-to-minute) on the peak load hours, and, its consequences on the electricity consumption by the end-users.

6. Acknowledgement

The authors would like to thank the Ympäristötili Pohjoista Voimaa foundation and the Thule Institute Research Programme for funding this research.

7. References

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