Modelling home electricity management for sustainability: The impact of response levels, technological deployment & occupancy

Jean-Nicolas Louis[a,*], Antonio Caló[a], Kauko Leiviskä[b], Eva Pongrácz[a]

[a]*Energy and Environmental Engineering, Faculty of Technology, University of Oulu, P.O.Box 4300, FI-90014 Oulu, Finland*
[b]*Control Engineering, Faculty of Technology, University of Oulu, P.O.Box 4300, FI-90014 Oulu, Finland*

Abstract

The evolution of electricity grids into a smart grid requires the inclusion of control systems to control load, flatten peaks and ensure the distribution of electricity. In parallel, the building sector will also be incorporating more control technology and put emphasis on sustainability issues such as reducing CO_2 emissions associated with the buildings electricity consumption. This article aims at modelling the residential sector and assesses the different levels of technology deployment to control the electricity consumption of household appliances. The number of inhabitants and their habits are also considered, and the response levels of users towards control systems are simulated. For this matter, a Markov-chain algorithm was developed for synthesising the electric load and introducing Home Energy Management System (HEMS). The emission levels from electricity consumption were assessed based on hourly CO_2 emission data from electricity production in Finland. Numerous electricity pricing models were also included, to assess the economic impacts of HEMS. The article suggests that a fully deployed HEMS may not be profitable for households with a low number of inhabitants. This is because the power consumption of appliances in stand-by mode offsets the positive impacts of HEMS on the electricity consumption profile.

Keywords: Simulation, Electricity usage, Smart building, Home Energy Management System (HEMS), Occupancy, User-response, Technological impact, Electricity pricing, Markov-chain, Sustainability

1. Introduction

The energy sector is under a vast change driven by legislation, aiming at reducing energy use and associated environmental impacts [1]. In the electrical sector, the smart grid represents the future, by allowing the integration of intermittent renewable energy sources into the energy mix [2]. Smart grid integrates a vast amount of disciplines including the communication field, Internet of Things, power engineering, control system engineering, and environmental engineering. Therefore, areas of focus and applications are multiple.

The European Union (EU) has enforced a set of legislations to tackle energy and environmental challenges driven by the change of infrastructure. The Renewable Energy Directive (RED) [3] establishes an overall policy for renewable energy, sets mandatory targets for the share of energy from renewables by 2020 and provides sustainability criteria for biofuels. Further, the objectives for 2020 also include a strategy for smart and sustainable growth, including energy system [4]. The three dimensions of sustainability are environmental, economic and social, which are defined together as the triple bottom line [5]. For firms, the triple bottom line means that they must balance their environmental, and social bottom lines in addition to their financial bottom line [6]. The sustainability of energy production should expand beyond the 2020 targets to all forms of energy [7]. The sustainability framework of RED only considers environmental indicators such as CO2 emissions and land-use impact. In this research, we included all three aspects of sustainability by considering also economic and social impacts of technology deployment, in addition to CO_2 emissions from electricity production.

The EU building sector consumes 28% of the total primary energy consumption, of which around 30% is for electricity generation [8]. Within the building sector, the residential sector is responsible for 60% of the total energy consumption [8] and has the best potential to impact on peak demand, characterised by the unpredictability of energy usage [9]. Smart buildings are an integral part of smart grids and their full potential is yet to be achieved. Smart buildings integrate a wide span of functions from health assistance, multimedia, everyday-life handling assistance, and energy management. In this research, we focused only on the energy management side, specifically on electricity consumption. In this context, the subject of our study is the Home Energy Management System (HEMS), comprised of sensors, computing systems, and a communication network. Whilst smart buildings can tackle energy consumption and peak shifting [10], the issue of concern is the impact of demand-side management and the response of end-users [11]. Modelling and pilot tests have earlier focused mainly on the benefits of automation technologies in homes, whilst the energy

*Corresponding author. Tel: +358 50 300 4344.
Email addresses: jean-nicolas.louis@oulu.fi (Jean-Nicolas Louis), antonio.calo@oulu.fi (Antonio Caló), kauko.leiviska@oulu.fi (Kauko Leiviskä), eva.pongracz@oulu.fi (Eva Pongrácz)

 doi:10.1016/j.enbuild.2016.03.012

used to run the system was disregarded. Research has recently been carried out to evaluate the impact of the automation system by extending the scope of studies and including the electricity consumption required by the system [12]. Van Dam et. al. [12] have found that energy management devices must reduce their energy consumption before they become economically and environmentally viable. However, their evaluation has been carried out in a static manner. There is need to carry out dynamic modelling, which integrates user specificities, different household sizes and levels of technology deployment.

For the modelling of the electrical demand profiles of dwellings, two distinct modelling techniques exist: the top-down and the bottom-up approach[13]. The top-down approach is more suitable for studying the general behaviour on a country level, whilst the bottom-up approach allows for a more detailed and flexible way of modelling the electricity consumption of individual users. The latter approach was used to model multiple dwellings where individual appliances were first aggregated to produce individual profiles, followed by an aggregation of the generated profiles to a large sample of electrical load under one node [14]. Appliance usage models rely either on the aggregation of measured data from multiple dwellings [15, 16], or on databases compiled for a specific country representing the overall market [17, 18, 19]. The advantage of using a database is that it bypasses the need for an extensive and exhaustive work of data collection. Once a database is compiled, statistical information are extracted and will serve as a basis to build the electrical demand profile of the system. Further, these statistics are traditionally used in probability distribution function, in support of stochastic methods for generating electricity load profiles [20, 21].

The end-use of the models lie in the technological influence on the electric load [22], and in the development of pricing models to enhance demand-side management (DSM) [23]. In addition, the environmental impacts associated with electricity consumption of the residential sector have been studied [24, 25, 26, 27], and the CO_2 emissions due to electrical appliance usage evaluated [28]. The limiting factor in these studies is that they are using fixed emission factors representing the overall yearly emissions of electricity production. More recent studies have included the hourly variation of the electricity production at the network level, however, still using fixed emission factors [29, 30]. The main drawback in using fixed emission factors is the lack of accuracy of emissions especially during peak load times, as well as in disregarding the feedstock price variations and their impact on the energy mix. Therefore, there is a need for a tool that can generate meaningful results evaluating technological influence, pricing models and environmental impacts of energy consumption in buildings. This tool must be able to interact with the different parameters that define a sustainable system. Appliance use also depends on the weather [31] and their impact on the house load varies based on their time of use and power ranking [32].

In this paper, we developed a Markov-chain model that allows creating artificial load consumption in dwellings in Finland. The outputs of the model include the electrical demand profile from the dwelling, the impact of pricing systems on the HEMS and, consequently, on the electricity demand and, finally, the CO_2 emissions linked to electricity consumption.

This study aims at creating a synthetic profile of electricity consumption in the residential sector including multiple technology level implementations for smart buildings. The output of the model will be compared with the daily and seasonal profile variations, as described in the Finnish Metering Decree (66/2009). Ultimately, the model can be used for generating scenarios of smart building impacts on the distribution network and to enhance micro-grid development in a sustainable manner. The developed methodology is described in Section 2 including the description of the inputs and the mathematical model, and Section 3 will discuss the results of the model.

2. Methodology

The model can be split into three categories: the inputs, the processes, and the output. The inputs include data of appliance use daily profiles, end-users characteristics, electricity grid state and electricity price, weather information, and the energy mix on an hourly basis. The model considered 21 appliances. Appliance characteristics such as power demand, identification number (ID) and the possibility of postponing use are listed in Table 1. Once the data are gathered, they will be used to create stochastic events. These events are further handled by the HEMS, including a simulation of user response. The HEMS relies on statistical information of household electricity consumption. Occupancy is considered as an output/input to the model considering also weather information and generated events. The two main outputs of the model are the power demand and the CO_2 emissions from the electricity consumption of the modelled house. Fig. 1 represents the workflow of the model and the sections where they will be further discussed.

2.1. Setting up appliance profiles

Appliances usage depends on multiple factors such as country habits, age and activity level of inhabitants [33]. In this pa-

Table 1: List of appliances used in the model with their related ID number and control options

House zone	Appliance	ID	Delay in use not possible	Short-term delay possible	Long-term delay possible
Kitchen	Washing machine	1		✓	✓
	Dishwasher	2		✓	✓
	Electric cooktop	3		✓	
	Kettle	4	✓		
	Electric oven	5	✓		
	Micro-wave	6		✓	
	Coffee machine	7		✓	
	Toaster	8		✓	
	Waffle iron	9		✓	
	Fridge	10	✓		
Bedroom	Radio	11	✓		
	Laptop	12	✓		
	Telephone charger	20	✓		
Bathroom	Electric heater	13		✓	✓
	Shaver	14	✓		
	Hair dryer	15	✓		
	Sauna stove	21		✓	
Living room	Television	16	✓		
	Stereo/Hi-Fi	17	✓		
Cleaning tools	Iron	18		✓	
	Vacuum cleaner	19		✓	

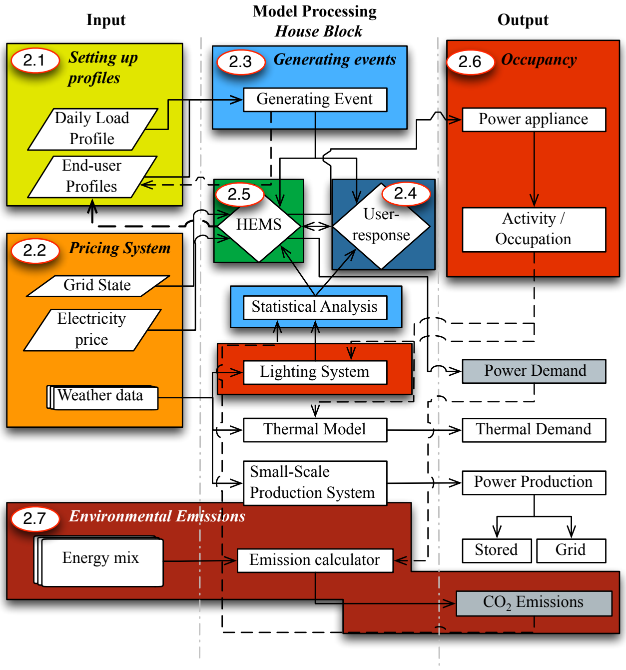

Figure 1: Box diagram of the model steps for simulating residential homes.

per, a reference profile of Danish and Norwegian appliance usage was used, as set up by the REMODECE project [34]. . The REMODECE project collected energy consumption data from multiple European countries to decrease energy use and carbon emissions in Europe. The hourly load profiles of Finnish households are taken from type load curve examples given in the Finnish Government decree on determination of electricity supply and metering 66/2009 (Metering decree). The load curve examples are given for three week-segments: weekdays (Monday–Friday), Saturdays, and Sundays for every month of the year. To generate daily and weekly appliance profiles, an algorithm was developed, and usage profiles (Γ) for all appliances were set based on the data of the REMODECE database as well as the Metering decree.

Further, daily energy consumption profiles (K_r) were defined based on REMODECE data. K_r is an *n-by-m* matrix profile [%] which is the daily statistical profile of the average power $\bar{P}$, average time usage $\bar{t}$, and average number of use $\bar{U}_w$ of a given appliance n within a week as shown in Eq.(1). The values of U_w,for each appliance, was defined following the Best Available Technology (BAT) defined in the EuP research tasks [35].

$$K_R = K_r \times \bar{P}\,\bar{t}\,\bar{U}_w \,\frac{52}{365.25} \qquad (1)$$

where K_R is an *n-by-m* matrix of the mean energy profile within a year [kWh/d], $\bar{P}$ is the mean power [kW], $\bar{t}$ is the mean cycle time usage [h], and $\bar{U}_w$ is the average number of use of a specific appliance in a week ['].

The daily energy consumption profile influences the daily distribution of energy K_p, , for a given hour and appliance. K_p is an *n-by-m* matrix [%], and it can be evaluated using Eq.(2).

$$K_p = K_R / S_{K_R} \qquad (2)$$

where S_{K_R} is an *n-by-m* matrix representing the hourly sum of all appliances of the mean electricity profile K_R [kWh/d].

Furthermore, the difference of variation between the reference daily load profiles K_v given in the Metering decree and the profiles created for one appliance must be known in order to correct the primary daily distribution profile. For this matter, the reference daily profile distribution of a given time slot (weekday, Saturday or Sunday) in a given month is multiplied by the daily electricity profile of the appliance.

$$D_{var} = K_v \sum_{h=1}^{m} S_{K_{R,h}} \qquad (3)$$

where D_{var} is a vector representing the difference variations considering the raw distribution function of each appliance [kWh/d], K_v is a vector representing the percentage variations between the REMODECE profile and the profile given in the Metering decree. Note that the sum of $S_{K_{R,h}}$ equals the total daily electricity consumption. Therefore, D_{var} is represented as the daily variation of electricity demand.

Consequently, the percentage variation between the daily distribution profile K_r and the reference profile is found as:

$$\Pi_{var} = D_{var} / S_{K_R} - 1 \qquad (4)$$

where Π_{var} is the percentage variation between both profiles [%].

The profile given in the Metering decree is higher than the one recorded for the REMODECE project. To reflect the difference between the two profiles, each appliance weighted in the profile is re-calculated according to the difference $K_{p,tot}$. 2.

$$K_{p,tot} = (1 + \Pi_{Var}) \cdot K_p \qquad (5)$$

where $K_{p,tot}$ is a *n-by-m* matrix of the total variation between K_r and the reference profile [%].

It will finally define the distribution function (PDF) of usability for each appliance described in the model (Fig.2). Finally, the daily profile for each appliance can be found in terms of electricity consumed and is defined as the normalised diagonal of the product between the difference of profile $K_{p,tot}$ and the cumulative sum of the hourly electricity profile as Eq.(6) illustrates.

$$K = diag(K_{p,tot} \cdot S^T_{K_R}) \cdot K_r / K_R \qquad (6)$$

where K is an *n-by-m* matrix representing the combined daily profile for each appliance [%], and Γ is its internal sum [%]. Γ is evaluated for each week segment and month of the year.

It is therefore possible to have the daily electricity distribution pattern for each appliance using this method. This will be used further in the model to trigger events at different time of the day.

 doi:10.1016/j.enbuild.2016.03.012

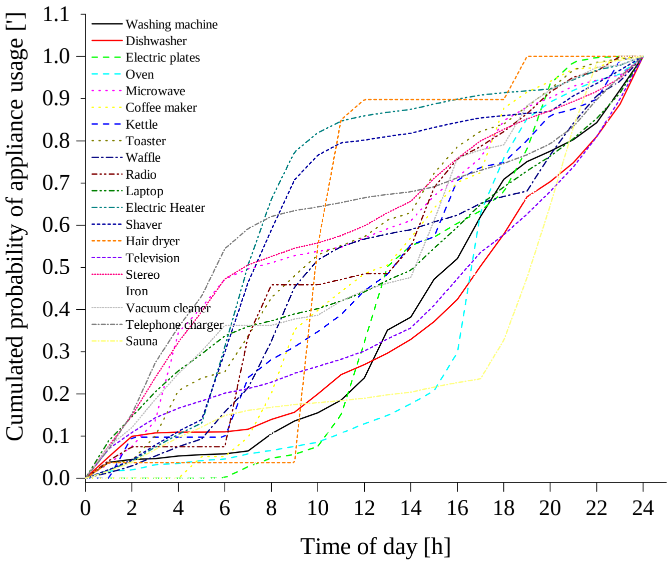

Figure 2: Probability distribution function (PDF) Γ for each appliance for weekdays in January.

2.2. *Pricing system*

In the Nordic countries, the price of electricity is subject to a tendering process where each electricity producer puts bids on the market. The bidding system closes at 18:00 and the hourly prices are fixed for the next 24 h. Furthermore, price signals are sent to electricity producers when the consumption or the production of electricity is too high, known as up and down regulating prices. Dynamic pricing on the distribution grid is provided by the Transmission System Operator (TSO) and is appearing and available for individual users. Therefore, three types of contracts are available for households: fixed price (FP), time of use tariffs (ToU), and real time pricing (RTP) based on the spot price [36].

The FP and ToU tariffs are restricted to only a few values as electricity providers set their price at different levels. In this article, three types of contracts were used: “Vihreävirta”, “Tuulivirta”, and “Varmavirta”. These contracts are offered by Oulun Energia Power Company. Vihreävirta is a carbon neutral, green option, based mainly on hydropower. Tuulivirta offers wind power, and is also zero carbon, Varmavirta is the cheapest option, and the electricity is produced mainly by Oulu´s peat-powered CHP power plant [37].

The popularity of the RTP system is growing rapidly and there are multiple commercial schemes available. Therefore, the model accepts lower and higher thresholds for limiting peak pricing with the possibility of implementing a fee based contract. As the price generation is a black box feeding to the HEMS, it is possible to implement other types of dynamic pricing that would include geographic location, network congestion, renewable energy penetration in the node, or any other influencing factor. Our earlier research investigated different schemes for billing individual consumers [36]. In this research, the spot price is used as the primary pricing system, to reflect real time fluctuation of electricity generation. The real time price $p_{h,h}$ can further be framed for every house in the model as $p_{h,h} \in [p_{h,h-min}, p_{h,h-max}]$.

The pricing model integrates the ToU pricing system, which is available for private consumers. Additionally, the model has information about the peak price periods in each season. The HEMS would suggests postponing device use during peak price periods. The likelihood that private consumers would comply (θ_{price}) is expressed with Eq.(7).

$$\theta_{price} = 0.9 \quad \forall \quad p_n \geqslant p \tag{7}$$

where p_n is the current price of electricity [Euro-cents], and p is the peak price of electricity [Euro-cents].

2.3. *Generating events*

In this section, each appliance that was selected as part of the household in the simulation is going to be processed. All the appliances that define the building are processed one by one iteratively. Multiple subtasks must be performed in order to generate an action. A simplified flowchart diagram, as drawn in Fig.3, describes the main steps of the algorithm. The algorithm is available as complementary information to this article. The first step requires getting statistical data from the processed appliance that includes the total activity throughout the simulation period, and its mean daily and weekly activity. The last two are input data into the simulation. Then, by extracting the limitations of usability of the appliance, the daily and weekly allowances for using the appliance are set. The usage will be further balanced for the weekdays and weekends acceptance variable. An hourly acceptance factor is set based on appliance profiles defined previously. Finally, an action can be generated for the processed appliance depending on if the above acceptability conditions are met. Nonetheless, the algorithm looks at the use-state of the appliance during the current iteration. In case the appliance is free to be used, the algorithm set the programme to be used by the appliance and will be reported to the next iterations.

The algorithm works based on the statistical previous usage of a given appliance. Therefore, the average usage of the studied appliance must be known to evaluate the weekly and daily usage. The purpose of knowing the activity frequency is to set allowance factors that will enhance the use of a given appliance.

2.4. *Synthesising user responses*

Three feedback strategies were implemented in the model including self-comparison, inter-comparison, and the electricity consumption target, each influencing the HEMS and the end-users in their decision-making [38]. The HEMS integrates the decision-making of the private consumers as well as the availability of devices and the possibility of postponing use.

Once the metering point aggregates all the information, it is possible to retrieve statistical data regarding end-user habits. In order to implement the decision-making process, four time levels will be used: mean daily, weekly, monthly, and yearly electricity consumption rates.

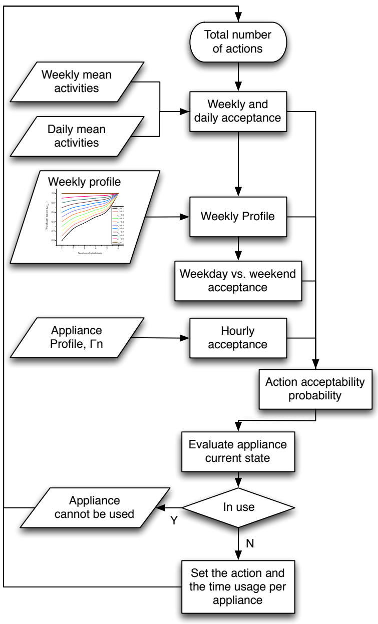

Figure 3: Flow chart diagram for generating events.

2.4.1. Self-comparison of historical consumption

The first type of comparison is between the actual electricity consumption and the average of historical consumption on the four time levels previously described. Depending on the case, two types of responses may occur. When the real-time consumption is smaller than the average, the user may not be convinced to reduce their energy consumption or to shift the load (Response = 0). When the real-time consumption has gone over the average, the end-user response will likely be positive (Response = 1). The response value does not mean that the end-user will always accepts or denies action, but affects the likelihood to carry out an action. The end-user's response also varies on different time levels; depending on average daily, weekly, monthly or yearly consumption. Monthly and yearly data are updated once a year at the end of the calendar year; however, monthly data are season-dependent. The equation expressing user willingness (χ_{self-i}) for all four time periods is:

$$\chi_{self-i} = 1 \quad \forall \quad E_i > \bar{E}_i \tag{8}$$

where i is the time period (daily, weekly, monthly or yearly), E is the electricity consumption during the studied time period [kWh/i].

In case the meter used is analogue, the user does not have access to the information of their electricity consumption, therefore the response is assumed to be zero ($\chi_{self-i} = 0$).

Once the self-comparison is carried out, the overall value of user willingness that will influence the end-user is evaluated. Three types of users are defined; "Green" users have a 70% positive response, "Orange" users 50%, and "Brown" users 30%. The response means that the likelihood the user implements the action recommended is on average between 30–70%. Depending on the feedback given by the HEMS, end-users' willingness level may be further amended by ± 2.5, 5, 7.5 or 10%. Therefore, a 70% average positive response rate is in reality in between 46% to 96%. The raise of awareness due to the knowledge on consumption θ_{self} can be quantified with the following equation.

$$\theta_{self} = U_r \left(\sum_{i=1}^{4} \chi_{self-i} \right) \tag{9}$$

where U_r is a 4-by-1 matrix representing the raise of willingness ['].

2.4.2. Comparison with other users

The second type of feedback is inter-comparison, when own consumption is compared with the neighbours'.While this method has received debated results, recent researches tend to support the fact that social influence impacts the energy consumption by motivating end-users to reduce their energy consumption [39]. Ayres et.al. [40] studied the impact of peer-comparison on a large scale using different feedback methods. Their results suggest that inter-comparison may decrease electricity consumption up to 2.5% from the baseline consumption. In our model, inter-comparison feedback method exists only if connections are made between buildings. Currently, the model requires that the houses have ID numbers in order to participate. However, they could also be grouped by location as all buildings have geographical coordinates. In case there is an aggregator in the simulation, it can disseminate the information to houses to similar profiles. Although the electricity consumption could be known and exchanged in real-time, it is not sensible as it involves a large bias and allows misinterpretation of the information; only monthly average electricity consumption is considered. In case the personal monthly average is over a given threshold, the likelihood of positive response increases. The raise of awareness due to inter-comparison ($\theta_{inter-m}$) is expressed as:

$$\begin{aligned} \theta_{inter-m} &= 1 & \forall \quad E_{inter} < c_s \bar{E}_m \\ \theta_{inter-m} &= 1 + r_a & \forall \quad E_{inter} > c_s \bar{E}_m \end{aligned} \tag{10}$$

where r_a is the raise of awareness [%], c_s is the threshold from which the awareness increases [%]. In the model, c_s is fixed to 1.2.

2.4.3. Target-based feedbacks

The third option implemented to influence user behaviour is the electricity consumption target setting. Although the efficiency of this method has shown to be lower [38, 41], it can enhance the user's motivation to reduce their electricity consumption by up to 5% [42]. It is possible to send signals to the end-users to warn them about overconsumption; the current concept is a fix daily limit when a warning is sent once the consumption goes above the defined limit [43]. This means that warnings would always occur towards the end of the day, whilst the limit should be changing and adapting to real time variation, to make use of potential savings made throughout the day. The first step to insert limitations and set goals to the end-user, it to define a referent percentage (τ_{ref}), by which the electricity

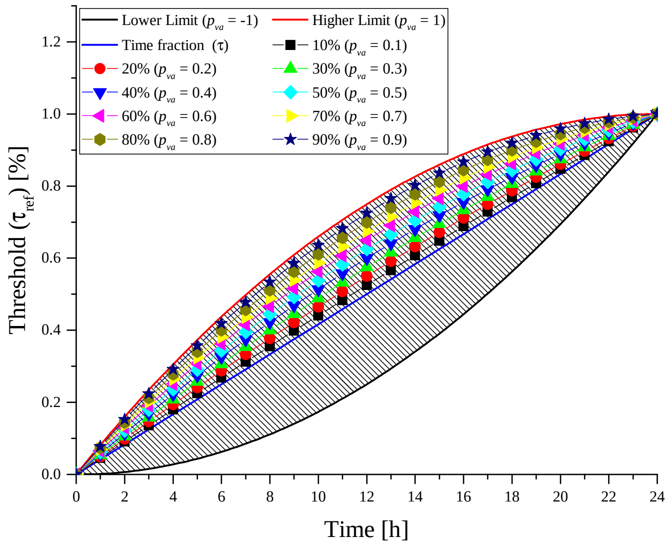

Figure 4: Referent percentage variations for setting electricity consumption target over a defined period of time, here for 1-day period ϱ with a time step t_{sl} of 1 hour.

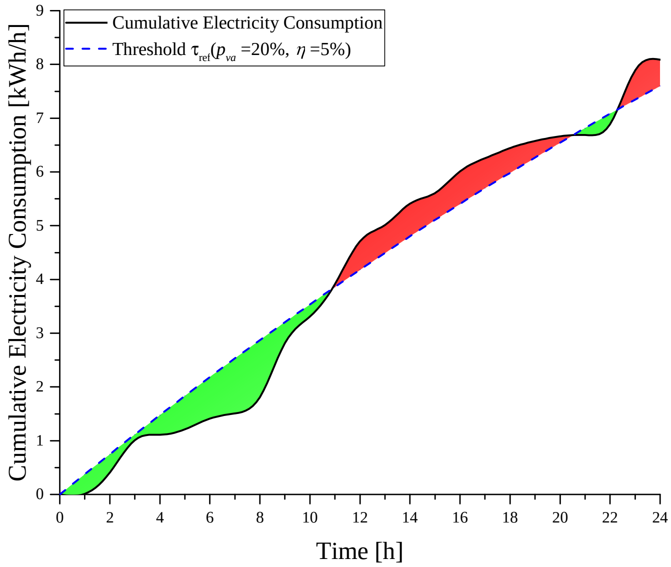

Figure 5: Cumulative electricity consumption over the day for a given appliance of a particular day in comparison with the threshold θ.

consumption could be decreased. The referent percentage is a function of time as shown in Eq.(12) and Eq.(13). The target system always makes a reference to the time period in which the end-users see their target set. For this matter, the period studied must be defined as a time fraction (τ_n)between 0 and 1, which represents the beginning and the end of the period studied.

$$\begin{aligned} \zeta &= \tau_{n-1} + \tfrac{t_{sl}}{1440\varrho} \\ \tau_n &= \zeta - \lfloor \zeta \rfloor \\ \tau &= \begin{bmatrix} \tau_0 \\ \vdots \\ \tau_n \end{bmatrix}. \end{aligned} \tag{11}$$

where τ_n is the time fraction of the studied period [%], t_{sl} is the time slot by which the target is revised [min], ϱ is the period [Day], τ is expressed as a $(1440\varrho)/t_{sl}$-by-1 matrix.

While the time fraction τ could be used for fragmenting the target electricity consumption, a linear approach is inappropriate and more amplitude should be given throughout the targeted period. Therefore, a second-degree polynomial is used for defining the referent percentage τ_{ref} that will be used to set intermediary targets, updated for each time slot t_{sl}. A representation of the different radius of curvature of τ_{ref} is illustrated in Fig.4.

$$\tau_{ref} = -\xi_{va}\tau^2 + (1 + \xi_{va})\,\tau \tag{12}$$

where τ_{ref} is the referent fraction of electricity consumption for every time slot [%], ξ_{va} is the feasibility of the system [%].

The target electricity consumption for the given period is further evaluated depending on historical consumption. In case the target reference period is set for each day of the week, a comparison is made using the historical consumption of the same day in past weeks. A ratio is set for each time slot t_{sl} defined previously over the targeted period ϱ. This ratio varies depending on the capability of the end-users to stay below the target. Finally the end-of-the-day targeted electricity consumption level ϖ [kWh/d], for the period ϱ is:

$$\varpi = \eta \bar{E}_\varrho \tau_{ref} \tag{13}$$

where η is the ratio by which the average daily electricity consumption can be reduced and depends on whether the user is able or not to reduce their electricity consumption [%], and E_ϱ is the average electricity consumption for the same day of the previous week [kWh/d].

In case the ratio between the target electricity consumption and the average electricity consumption of a particular day is smaller than the ratio they should have reached, then the response from the user is not likely to change. If, however, the current electricity consumption is greater than the target, it will provide additional motivation and, concurrently, the targeted electricity consumption is reset to a lower expectations. The response level on target based study, $\theta_{target-\varrho}$, is defined as:

$$\theta_{target-\varrho} = 1.1 \quad \forall \quad \frac{\varpi}{\bar{E}_\varrho} > \tau_{ref} \tag{14}$$

where E_ϱ is the mean electricity consumption on the studied period [kWh].

Consequently, the electricity consumption of end-users will be closing the targeted level to the degree of user response level. Fig.5 is an example of the cumulative daily electricity consumption of a simulated house compared to the target imposed on the end-users.

Finally, once all the variables defining the response level depending on the chosen feedback method are quantified, they will be integrated to the end-user definition U_r set for the three user types ("Green", "Orange", "Brown"). The user-response is therefore influenced by the feedback system. It implies that the behaviour of the private consumers can be modified depending on the feedback strategies. The change of behaviour varies from 0 to 33%of the original willingness towards influencing reduction in electricity consumption. It results in the evaluation of a dimensionless figure of the private consumer's willingness θ.

$$\theta = U_{res} \cdot \theta_{target-\varrho}\theta_{inter-m}\theta_{self}\theta_{price} \tag{15}$$

where U_r is the basic user response defined in Section 2.4.1. θ_{price} was defined in Eq. (7).

While the acceptance of the private consumers could increase or decrease depending on the feedback given on their electricity consumption, there is always a certain probability that the private consumer would refuse to undertake the action. Therefore, the willingness of undertaking an action is placed in perspective with a random number that will adjust the final response of the private consumer. The final response θ_f will be in the form of a Boolean:

$$\theta_f = 1 \quad \forall \quad R_h \sim (0,1) > \theta \tag{16}$$

where R_h is a random number generated between [0,1].

2.5. Home Energy Management System (HEMS)

The HEMS includes multiple components for managing the energy consumption/production of households. One of the HEMS'components is the controller, which will evaluate the possibility to postpone events depending on the control options of appliances (as listed in Table 1), and integrate end-user preferences. In our model, the controller will integrate time stamps, generated events, the metering system, user type, user response, and the electricity pricing system. The controller is aware of the electricity contract used, which will determine the price of electricity and provide price forecasts.

There are multiple types of metering systems available on the market. Each of them have targeted functions and general functionalities as summarised in the CEN/CLC/ETSI/TR 50572:2011 technical report on functional reference architecture for communication in smart metering system [44]. These functionalities range from simple reading system to HEMS enablement. In our model, the following four options are used:

– Option 1: A basic metering system that does not provide any information to the end-user, only reports periodically electricity consumption information to the electricity producers or the DSO;
– Option 2: A smart meter that integrates only the Functionality 1 and 2 of the smart metering system as defined by CEN/CENELEC/ETSI standard [44];
– Option 3: A smart metering system that is able to provide feedback to the end-user and integrates F1, F2, F3, F5, and F6 functionalities. However, it does not include functionality F4 for home energy management;
– Option 4: Integrates all functionalities F1—F6, as defined by the standard, so it also includes direct control of appliances.

The appliances can be controlled in three ways:

(i) Delaying an action to another time slot based on selected criteria i.e. economic, environmental;
(ii) Reducing the power demand (for instance in case of a kettle, we are influencing the resistance of the boiler);
(iii) One-hour delay in case long term shifting is not available. For instance, it is unlikely that sauna use would be postponed with several hours.

The time slot where an action can be postponed depends on the electricity price and environmental emissions. For example, when using the ToU or FP systems, the primary factor for postponing an action would be reducing CO_2 emissions. In contrast, in case of RTP system, price is the primary factor for postponing an action. In case of RTP, the number of hours t_d by which an action can be postponed is defined as:

$$t_d = min\left[F_{p_{h,h}}\right]_{h_1}^{h_2} \tag{17}$$

where $F_{p_{h,h}}$ is a vector of 1-by-n representing the forecasted price vector, and h_1 is the starting hour and h_2 the ending hour [h] that will frame the search.

While the decision about postponing an action is largely dependent on end-users willingness, in case it is not a critical action, in option 4, the HEMS can make the postponing decision. The number of time periods $d_{h,l}$, when an action can be delayed is defined as:

$$d_{h,l} = \theta_f t_d \tag{18}$$

where t_d is defined in Eq. (17), and θ_f in Eq. (16).

Postponing device use on a long-term does not necessarily apply when there is no automation, neither when there is no smart metering system.

In the following sections, variables D_S and D_ρ will be Booleans given for each appliance, D_S represents the short-term delay, and D_ρ long-term delay.

2.5.1. No Delay Case

In case of no delay or when an action is already on-going for the given appliance, the final action $\Upsilon_{final,n}$ equals the time usage of the appliance $t_{a,n}$.

$$\left(D_S = 0 \vee D_\rho = 0\right) \wedge (v_c = 1) \rightarrow \Upsilon_{final,n} = t_{a,n} \tag{19}$$

where v_c is a Boolean representing the use state of an appliance.

2.5.2. Short-term delay case

Short-term delay means not more than one hour and it is a factor of appliance type and user acceptance. The likelihood of short-term delay is a variable of the knowledge accumulated, and signal from the grid if it is a sensitive time for the electric network. Whether and how long the use of a device can be postponed is defined as follows:

$$D_{S,n} = D_S \cdot d_{h,s} \tag{20}$$

where $d_{h,s}$ is the number of time period by which an application can be postponed.

When delay is possible ($D_S = 1$), condition g_1 and g_2 will need to be ascertained. At first, it is necessary to check whether the current iteration has triggered an action for the given appliance as seen in Eq. (21). If an action has been triggered during the previous iteration, the new action that represents the remaining action from the previous iteration is postponed to its right time.

$$\begin{gathered} g_1 = (D_S \neq 0) \wedge (t_{a,n} > 0) \\ g_2 = (D_S \neq 0) \wedge (D_{S,n-1} > 0) \wedge (t_{a,n-1} > 0) \\ g_1 \rightarrow \begin{cases} g_1' \,(t_{a,n-1} = 0) \\ g_1' \rightarrow \Upsilon_{final,n+D_{S,n}} = t_{a,n} \\ \sim g_1' \rightarrow \Upsilon_{final,n+D_{S,n-1}} = t_{a,n} \end{cases} \end{gathered} \tag{21}$$

In case the first condition is not met, then the algorithm is looking at whether or not an action has been triggered in the previous iteration and if the previous had a short term postpone action. In this case, the current action to be triggered is moved to the previously postponed time. If none of the abovementioned conditions are met, then the final action will be either equal to an action that has been triggered without delay or no action at all (Eq. (22)).

$$\begin{gathered} \sim g_1 \rightarrow g_2 \rightarrow \Upsilon_{final,n+D_{S,n-1}} = t_{a,n} \\ \sim g_1 \rightarrow \sim g_2 \rightarrow \Upsilon_{final,n+D_{S,n}} = t_{a,n} \end{gathered} \tag{22}$$

2.5.3. Long-term delay case

Some appliances, such as the dishwasher or the washing machine, may be postponed by a longer time.

In the following section, we want to offset an action in case the automatic controller has been engaged. Three variables need to be defined in order to locate in the array the position where the simulation is and where it should shift the action depending on the situation. $D_{p,n}$ represents the number of steps forward that an action is to be delayed, and t_n is the appliance programme chosen.

First of all, we want to know if there is an existing programme that has already been re-scheduled by evaluating h. If an action has already or just been triggered and no future schedule has been planned, then the time to which the appliance is to be re-scheduled follows the time $d_{h,l}$ set by the controller.

$$\begin{gathered} h = \left(\textstyle\sum_{i=n}^{\infty} \Upsilon_{final,n} = 0 \;\wedge\; t_{a,n} > 0\right) \\ h \rightarrow D_{\rho,n} = n + d_{h,l} \\ \sim h \rightarrow D_{\rho,n} = 0 \end{gathered} \tag{23}$$

Furthermore, the system will also evaluate υ the sum of actions between the time to which an appliance could be postponed and the related time of use of this appliance that has been previously programmed.

$$\upsilon = \sum_{n=D_{\rho,n}}^{D_{\rho,n}+\lceil t_{a,n} \rceil} \Upsilon_{final,n} \tag{24}$$

where n is the simulation step starting from 0, υ evaluates if the appliance has not been already switched to the evaluated time ['].

Thus, υ is positive if an action for the studied appliance has already been re-scheduled and equal to 0 if the time slot is empty.

It is now possible to evaluate the time period to which an action should be postponed. The general algorithm would postpone the action to the appropriate time slot, however a series of exceptions occur while operating the algorithm. Four conditions must be checked ending up to different consequences on the action schedule as presented in Eq. (25). The first condition i_1 is checking if no actions have been scheduled forward. The second condition i_2 is checking whether the long-term delay variable is active or not and whether the current iteration has triggered an action to be eventually postponed. The third condition i_3 is looking at the previous postpone statements and at the previous action triggered. Finally, the fourth condition i_4 checks whether the studied appliance has already a reserved time period for later use.

$$\begin{cases} i_1 = (\upsilon \neq t_n) \\ i_2 = (d_{h,l} > 0 \;\wedge\; t_{a,n} > 0) \\ i_3 = \left(D_{\rho,n-1} > 0 \;\wedge\; t_{a,n-1} > 0\right) \\ i_4 = \left(\Upsilon_{final,n} > 0\right) \end{cases} \tag{25}$$

The combination of conditions checked as presented in Eq. (26), Eq. (27), and Eq. (28) define the value where the action is going to be postponed and therefore redefines the action vector that will serve as a base for determining the value of the action $\Upsilon_{final,n}$.

$$i_1 \rightarrow i_2 \rightarrow \begin{cases} i_2' = (t_{a,n-1} = 0) \\ i_2' \rightarrow \Upsilon_{final,D_{\rho,n-1}} = t_{a,n} \\ \sim i_2' \rightarrow \Upsilon_{final,D_{\rho,n}} = t_{a,n} \end{cases} \tag{26}$$

$$i_1 \rightarrow \sim i_2 \rightarrow \begin{cases} i_3 \rightarrow \Upsilon_{final,D_{\rho,n-1}} = t_{a,n} \\ \sim i_3 \rightarrow \Upsilon_{final,D_{\rho,n}} = t_{a,n} \end{cases} \tag{27}$$

$$\sim i_1 \rightarrow \begin{cases} i_4 \rightarrow \Upsilon_{final,n} = t_{a,n} \\ \sim i_4 \rightarrow \Upsilon_{final,n} = 0 \end{cases} \tag{28}$$

The power output from the studied appliance can be evaluated once the action $\Upsilon_{final,n}$ has been evaluated. The nominal power $P_{i,a}$ of the appliance is determined by the EuP Directive [45]. Further, the electricity used during the elapsed time period, which is calculated by multiplying the nominal power of the appliance with the time step chosen for the simulation, is calculated as:

$$\left(\Upsilon_{final,n} = 0\right) \rightarrow E_h = P_{i,a} \cdot \Upsilon_{final,n} \tag{29}$$

where $P_{i,a}$ is the power output of the appliance in active mode depending on the power rank of the appliance used [kW] and E_h is the electricity consumption of the studied appliance [kWh/h].

If an action does not occur at $t = n$, the appliance may be in a different state such as in stand-by or off-mode. In order to evaluate the state the appliance is currently in, the use of statistical information is integrated into the model. Indicative data from the eco-labelling reports are used with a normalized random number R_s ($R \sim ([0, 1])$) that will, at each iteration, evaluate the state in which the appliance is:

$$(R_s < \varphi_s) \rightarrow E_h = P_{i,s} \tag{30}$$

where φ_s is a variable defining the percentage of time spent in stand-by mode compared to the off-mode [%], and $P_{i,s}$ is the

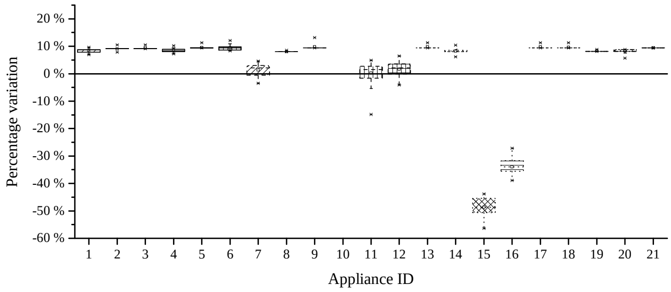

Figure 6: Occurrence of the appliance usage per week for 96 simulated houses compared to the maximum usage allowance set as an input in the simulation model.

power output in stand-by mode depending on the power ranking of the appliance [kW].

If the appliance is not in an active use and is found to be in stand-by mode, then the power output will be the appliance's power rating in stand-by mode. If the appliance is in an off-mode, then the power output takes the value of the off-mode power $P_{i,off}$ ($E_h = P_{i,off}$). In every other situation, the output power of the appliance is set to zero. The occupancy scenario is deduced from the power output of the house.

Ultimately, the model outputs multiple results such as the detailed usage of each appliance as a function of maximum weekly usage. Fig. 6 illustrates the statistical spread of the appliance usage for a given house. It can be observed that the mean weekly usage per appliance converges with the maximum weekly usage (U_w) given as an input to the model. Some of the appliances such as the hair dryer or the television are used half of the maximum allowed time while most of the appliances are in a range of +5% use over the maximum allowed weekly usage. This figure stays in the uncertainty set in the model as +10%.

2.6. Occupancy

The occupancy scenario is not given as an input to the simulation tool as the model relies on the appliances usage based on probability distribution functions. Nonetheless, occupancy may be crucial when studying the heat load and ventilation according to humidity variation within a building [46]. In our model, occupancy is defined by the appliance usage profile. Depending on whether or not a set of appliance is considered active, the occupancy is deduced from it and the lighting scenario is set accordingly. Therefore, the input data of the simulation are the standby power P_{Stb},the type of light bulbs (incandescent or low-energy), and the building area A_{Buil}. To evaluate if artificial light is required, we calculate the relative illuminance E as follows:

$$E = \frac{E_v - E_{min}}{\frac{2}{3} \cdot E_{max}} + X_{min} \tag{31}$$

where E_v is the external illuminance [lux], E_{min} and E_{max} are the minimum and maximum levels of natural light [lux], and X_{min} defines the minimum probability of using artificial light for a given illuminance ['].

Occupancy V_{Occ} is a Boolean and is determined by comparing the actual electricity consumption to standby power.

$$V_{Occ} = (P_{Tot} > P_{Stb}) \wedge ((1 - E) \geq R_l \sim U(0, 1)) \tag{32}$$

The output power of the lighting system (P_l) is defined by the type of light bulbs and the building area.

$$P_l = V_{Occ} \times A_{Buil} \times P_{Tech} \tag{33}$$

where P_{Tech} is the installed power of the lighting system [W/m^2], and A_{Buil} is the building area [m^2].

In case the actual consumption equals the base load, the dwelling is considered empty and the output power of the lighting system equals zero. If the consumption is higher than the standby, the house is considered occupied and the relative illuminance E is used.

2.7. CO_2 emissions from electricity production

One of the novel inputs of this simulation model is the inclusion of CO_2 emissions related to the electricity consumption of the house. Traditionally, in such models, fixed emissions factors are used based on yearly averages. This is an imprecise method as the type of power generation and fuels varies seasonally and even within a day. Additionally, Finland as insufficient capacity for satisfying overall demand, therefore 16% of electricity demand is imported from neighbouring countries. If HEMS is to reduce peak time emissions, we need to have a more accurate information of actual CO_2 emission profile. For this purpose, in this article we use a dynamic model previously developed by the author [47]. This dynamic model calculates CO_2 emissions on an hourly basis, using actual statistics of power plant use from Fingrid Oyj (the Finnish TSO) and their primary use of fuel reported to Finnish Energy. Real-time CO_2 emissions reflect the variation of fuel used in electricity production. Additionally, we consider not only the primary energy sources from domestic electricity production but also the emissions from the electricity of trading countries. The latter is defined using the electricity profile provided by the Nord Pool Spot power market. This means that the CO_2 emissions impact of household electricity consumption varies hourly, therefore, the HEMS is better adapted for providing feedback on actual environmental impact and reducing peak time emissions.

3. Results and discussions

Simulations have been carried out under multiple conditions, including multiple types of users, numbers of inhabitants and energy efficiency levels of appliances, and user quality. In order to validate the model, the profiles generated need to meet the constraints set in the inputs of the model such as the frequency of appliance usage, overall profile variation and seasonal electricity demand variation.

The output of the model is a set of indicators reflecting on the performances of buildings:

Table 2: Electricity consumption and emissions for houses with different number of inhabitants.

inhabitants	Emissions				Energy	
[']	[KgCO2/y]	[KgCO2/kWh]	[KgCO2/kWh/p]	[KgCO2/y/p]	[kWh/y]	[kWh/y/p]
1	234.72	0.12641	0.13	234.72	1851.56	1851.56
2	322.84	0.12602	0.06	161.42	2570.47	1285.23
3	501.54	0.12420	0.04	167.18	4034.89	1344.96
4	706.48	0.12539	0.03	176.62	5637.59	1409.40
5	838.09	0.12364	0.02	167.62	6774.82	1354.96

Table 3: Annual consumption variations

Metering System	Number of inhabitants				
	1 Person	2 Persons	3 Persons	4 Persons	5 Persons
Option 1	0.00%	0.00%	0.00%	0.00%	0.00%
Option 2	0.08%	-0.32%	-1.04%	-2.72%	-2.12%
Option 3	15.93%	12.07%	7.45%	3.52%	3.75%
Option 4	15.90%	12.00%	7.30%	3.26%	4.15%

- Overall electricity consumption of the simulated house on an hourly basis - this is due to the fact that most metering systems have a time step of 1 h for transferring information, while some intend to have a sampling period of 15 min;
- Occupancy of the house;
- Related electricity price–used by energy retailers for billing the end-user;
- CO_2 emission levels of the simulated house.

Each indicator is used as an input to the house for decision-making purpose of the HEMS.

3.1. The profile Generated

The objective of the modelling was to match the reference profile to that of the Metering Decree (66/2009). Further, we evaluated the percentage variation of the generated profiles from the reference profile for different household sizes and the four levels of automation. The mean of the percentage variations are compared with the reference profile as summarized in Fig. 7. Four time periods can be distinguished in the results. During 00:00–5:00, there is an overestimation of 7.3% compared to profile given in the Metering Decree. The absolute difference is 0.15% for the same slot. During 6:00–14:00, there is a relative under-estimation of approximately 15.6%, or 0.65% in absolute values. During 15:00 –21:00, the average over-estimation is 10.5%, and the 0.66% absolute value. Finally, during 22:00–00:00 the under-estimation is 10.3% on average, or 0.39% in absolute values. This is considered to be an acceptable margin of uncertainty bearing in mind that the variation in the daily profile is small.

The seasonal variation of electricity consumption is to be highlighted; Figs. 7 (b) and (c) detail the daily profiles in December and June, over 3 weekly segments: the weekday, Saturday, and Sunday. While the evening peaks are more pronounced due to the use of sauna-stoves, the electricity consumption profiles generated show an evenly distributed use of appliances among the weeks and months.

CO_2 emissions reduction is one of the main drivers for implementing new technologies in the residential sector. To this effect, hourly emission data were aggregated weekly to evaluate the emissions level of the dwellings as illustrated in Fig. 8. While the emissions present a similar profile at different levels, this is due to the fact that the simulated houses had the same profile input.

When considering the emissions in terms of inhabitants, the larger the number of inhabitants, the lower the yearly emission factor becomes as shown in Table 2.

As Table 2 indicates, the lowest impact occurs for two-persons households while the highest for households with a single inhabitant. Considering the growing number of single inhabitants in attached houses (43.45%) and block of flats (58.88%) added with the 1% yearly increase of surface area per inhabitants in Finland, these mount up to an alarming trend of growing household related CO_2 emissions [48, 49].

3.2. The influence of HEMS

In order to assess the impact of HEMS, three criteria must be compared: the annual electricity consumption, the daily load profile, and the CO_2 emissions impact. To evaluate the impact of different technologies on the annual electricity consumption, a comparison with the standard metering system is necessary. Table 3 summarises the influence of the 4 metering systems on the annual electricity consumption.

It can be noted that the higher the technology level, the greater its impact on annual electricity consumption. The reason is that the smart metering system and the (automation of the) appliances must exchange information on a regular basis. The power consumption from the sensing network was integrated using 3 modes: active (transmitting or controlling the plug), stand-by (collecting data only), off-mode (inactive). In case of the smart meter, a data transfer every 25 min is considered, meaning that the rest of the time the smart meter collects electricity consumption data or is in low power consumption mode. The sensors exchange information with the central unit every 10 s. While the power demand during the communication period is high, the transmission time is 200 ms. This means that the majority of electricity consumption occurs when the devices are in low consumption mode. The smart meter is rated at 20 W in active mode and around 5 W in idle mode (when recording the data but not sending information). Every sensor is rated at 4 W in active mode and <1 W in idle mode. Depending on the number of sensors in the network, the yearly consumption of the HEMS can go up to 350 kWh/y. Secondly, the number of inhabitants affects the overall electricity consumption of the deployed technology. A one-person house may see its overall annual electricity consumption raise by over 15.9% when a fully automated system is deployed compared to a regular metering system without automation. In contrast, a five-person household will experience a 4.1% annual electricity consumption rise in the same configuration. When considering only smart metering option 2, which what is already being deployed across Europe, the annual overall electricity consumption of a one-person dwelling will raise by 0.08%, while of three-person households the electricity consumption will declining up to 1.04%. This shows that the impact is mainly due to automating the entire pool of appliances within the home, and adding sensors to all appliances. Our results are consistent with van Dam et. al [12]. Most research focuses on the absolute

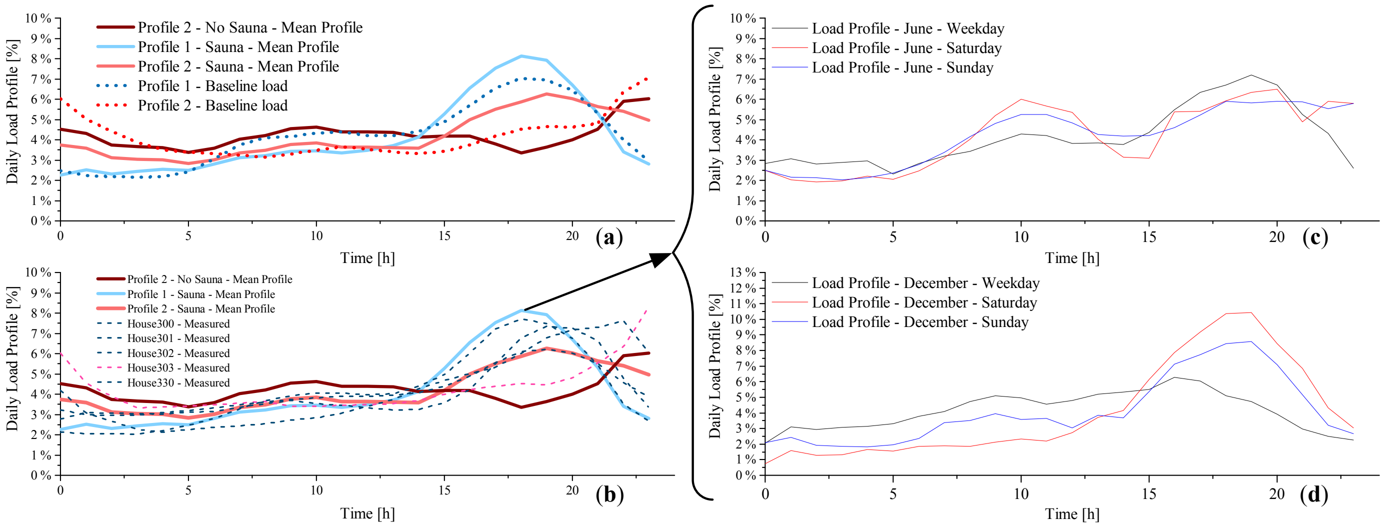

Figure 7: Average daily profiles expressed as a percentage change for non-controlled simulated households compared to (a) the average daily profile set as an input in the simulation model, and (b) to measured houses. Detailed load profiles for (c) June and (d) December.

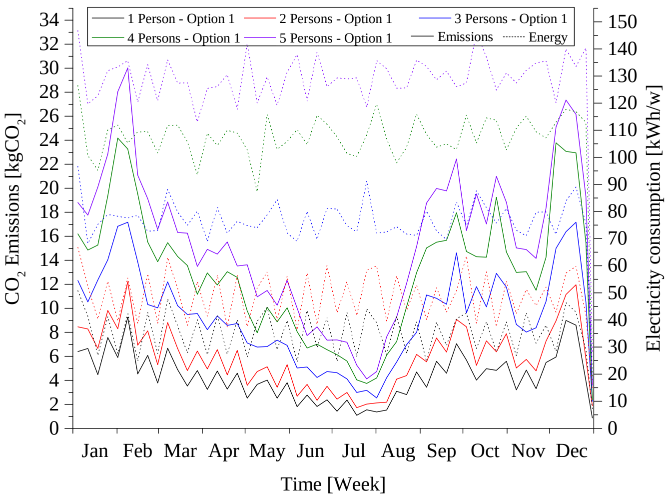

Figure 8: Weekly cumulated CO_2 emissions and related electricity consumption for 5 types of houses.

benefits of HEMS and excludes its energy need for running. In order to benefit from the improved monitoring system, we need to implement more automation. However, when we have more advanced control and feedback systems, the overall energy demand also increases. In our model, the assumption was made that every appliance was monitored. Consequently we see an increased energy demand due to the HEMS.

Another aspect that must be evaluated is the impact of the technology on the average daily load profile of the dwellings. The first way to look at it is by evaluating the relative changes in the daily load profile as illustrated in Fig. 9.

It can be observed that no matter the number of inhabitants in the house, the average daily load profile is getting flatter while the technology level deployed is raising. The transfer of power demand contributes to the flattening of the daily load from the evening period to the night period. While the statement of the power shifting is true in any case in terms of relative change in the power demand on the daily load profile, the absolute daily profiles, as presented in Fig. 9, suggest that load decrease occur for households of three persons or more, while with households with two inhabitants or less will have an increased power demand. It can be hypothesized that while smaller households have lower electricity consumption rates, they have lower flexibility due to lower ownership level of appliances. It is correlated by Ippolito et al. [50]who found that automation systems have a greater impact when the original energy consumption is high and the energy class is lower. Therefore, it can be concluded that the HEMS affects positively the shape of the load profile, no matter the number of inhabitants in the house, by shifting load from evening to night times. However, the HEMS increased the overall power demand for single person households.

3.3. User response sensitivity

User response to technological deployment is integrated into the model as expressed in Section 2.4. The user response index simulates end-users interaction with the HEMS and, therefore, defines to what degree the automation system can impact on electricity consumption and related CO_2 emissions. Three types of user response levels were set in the model: "Green" households are positive responders, with an average positive response level of 70%, "Orange"households have 50% response level, and "Brown" households 30%. Fig. 10 illustrates electricity consumption and CO_2 emission levels for these three user types, depending on the number of inhabitants and the level of technology deployment. Additionally, the difference of response levels is expressed as percentage variation of emissions and electricity savings achieved.

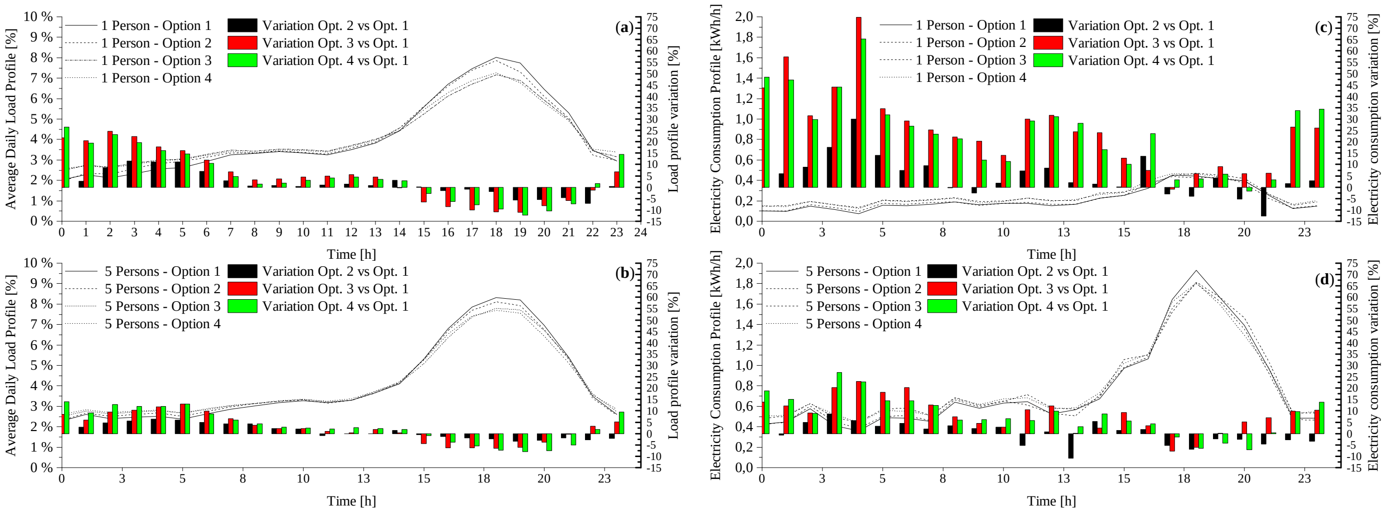

Figure 9: Relative daily profile variation for 4 metering systems for (a) 1, and (b) 5 persons; absolute daily profile variation for 4 metering systems for (c) 1, and (d) 5 persons.

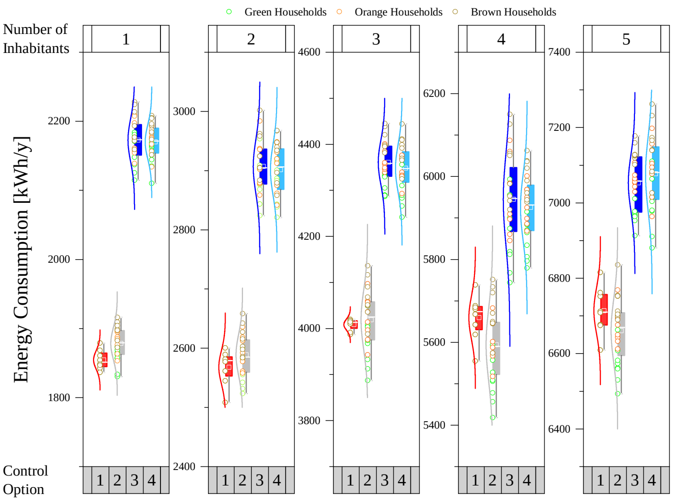

Figure 10: Electricity consumption for three household types, and four levels of the technology deployment by the number of inhabitants.

On average, the electricity consumption difference between "Green" and "Brown" househols is 2.27% (σ = 0.0037) and for CO_2 emissions the difference is 2.31% (σ = 0.0036).

Recent research highlighted the importance of feedbacks to end-users and their effect on load shifting and electricity consumption [30, 51]. Our simulation results are consistent with the finding of Nilsson et al. [30]: the impact of information system on load shifting allowed shifting peak load to off-peak period by 5% on average. Notwithstanding, feedback on its own did not impact the electricity consumption significantly.

3.4. Price variation

The model includes eight main contracts that can be selected as an input to the simulation. The pricing is used as an input to the HEMS for controlling the appliances. Therefore, each contract influences (the HEMS) in a different manner the electricity usage, CO_2 emissions levels, and the electricity bill. In addition to the eight contract types, three types of HEMS systems and five types of household sizes were considered. The indicators are further categorised between the annual electricity consumption, the annual variation of the electricity bill, and the related annual CO_2 emissions. The indicators weigh the variation of the impact from each contract type on one to another and are further summed up to form I as Eq. (34) illustrates.

$$I = \frac{\sum_{n=1}^{y}\left(\frac{x-x_{max}}{x_{min}-x_{max}}\right)_n}{y} \tag{34}$$

where x is the variation of a specific variable [%], and y is the number of indicators considered ['].

The global indicator I is summarised for every type of contract in Fig. 11. Fig. 11 illustrates the cross-comparison of different contracts by types of electricity bills, number of inhabitants, and metering system on the annual electricity consumption, bill and CO_2 emissions.

Real time pricing (RTP) had the greatest impact on the annual electricity bill compared to other pricing mechanisms. RTP without price limitation decreases the electricity bill by 28.5% on average, while the RTP with a limitation at 8.6 Euro-cents/kWh reduces the electricity bill by 21.3% on average. Furthermore, the difference between the limited and non-limited RTP is around 5.8%.

The influence of the RTP on the annual electricity bill can be noticed in any kind of configurations, from no smart metering system to fully deployed HEMS, and for any number of inhabitants.

The average value of I for RTP without limitation is 0.538, which is the best alternative when considering annual electricity consumption, price and emissions. RTP with a limitation of 8.6 Euro-cents/kWh and the three types of Time of Use (ToU) tariffs "Varmavirta", "Tuulivirta", and "Vihreävirta" fol-

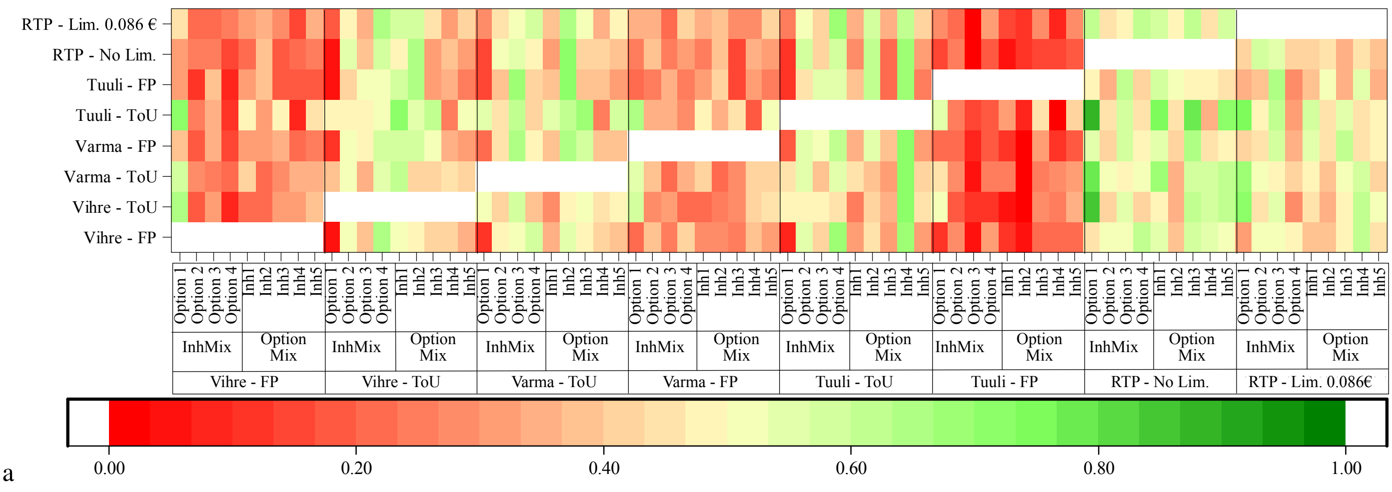

Figure 11: Cross-comparison of the different contracts, by number of inhabitants and by metering system on the annual electricity consumption, annual electricity bill, and annual CO_2 emissions.

low closely with indices of 0.484, 0.459, 0.447, and 0.444 respectively. The contracts using Fixed Price (FP) have the lowest indices, 0.330, 0.293, and 0.197 respectively. Despite the fact that the RTP has a great positive impact on the annual electricity bill, it had the fourth and fifth best score for its impact on electricity and annual CO_2 emissions with indices of 0.429 and 0.368 respectively. As the indicators' weighs are identical, the impact on the annual electricity bill balanced the average results of the RTP without limitations, thus the high index levels. Finally, the contract that shows the most stable results is the ToU tariffing system from “Varmavirta”, as it ranked highest for its impact on the annual electricity consumption and its related CO_2 emissions, but only third for its impact on the annual electricity bill.

4. Conclusions

In this paper, a simulation tool was developed for evaluating the influence of technology level deployment, pricing models, and CO_2 emissions related to the electricity consumption on an hourly basis. The model included a simulated house, with twenty-one individual appliances that can be replicated multiple times, and three types of end-user profiles. The inputs of the model were appliance daily load profiles, end-user profiles and electricity prices. The model also generated events based on daily load profiles, simulated different levels of HEMS options and user responses.

The model was successful in generating valid profiles that matched the input values from appliances and occupants’requirements. The profile generated also showed consistency in the daily variation of the load depending on the number of inhabitants. Seasonal, and weekly variations based on the demand and the weather conditions were included as well.

The simulated HEMS impacted positively on the overall load profile by flattening the demand, through postponing appliances usage throughout different time slots. The CO_2 emissions associated with electricity consumption showed to be dependent on the number of inhabitants; the per capita emissions were lowest for two-person households and highest for one-person dwellings. Nonetheless, the impact of the technology on the electricity consumption, the CO_2 emissions and the pricing model increased. This is mainly due to the fact that all appliances are connected with smart plugs, which have a rather high energy consumption and therefore impact negatively the overall electricity load. Therefore, until highly energy efficient sensing technologies come into the market, the fully monitored and automated homes for electricity consumption management cannot be seen as an option to reach European energy efficiency targets.

The pricing model tends to favour RTP without limitations, as its impact on the yearly electricity bill is greater than any other pricing model. On the other hand, RTP performed worst in terms of reducing net CO_2 emissions. The integration of the environmental component into the RTP model needs to be further investigated. However, the indices for ToU tariffs are more uniform for the three indicators.

The model presented in this paper can have multiple implications in terms of policy and technology development strategies. For the future, it would be useful to have a tool that simulates microgrids by including a number of houses and their inter-communication. It is foreseen that this model will be further used for microgrid model development. The model did not aim at synthesising the electricity load for network development and, therefore, it may not be useful for analysing fast change in the electricity network. Currently, only a limited number of appliances were included into the library, however, the model allows including more appliances. One of the advantages of the model is that it is flexible and can be adapted to all residential building types. The thermal load of dwellings was not included in the scope of this model; in the future, the district heating system will be integrated to evaluate the synergetic relationship between multiple energy vectors. In this paper, we have not considered how end-user characteristics (e.g. childrens age, income level, employment, health, etc.) influence their electricity consumption. These variables could be further integrated in order to extend the panel of end-users. Finally, the ultimate goal is to develop a sustainability index for evaluating the energy management system of dwellings that includes wider considerations of environmental, social and economic impacts.

5. Acknowledgement

Funding provided by the Thule Institute Research Programme, the Academy of Finland (Decision №287748), and the Fortum foundation (Grant №201500108).

References

[1] Office, Publications, on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC, European Commission (2009) 1–47.

[2] M. Sanchez Jimenez, Smart Grids: from innovation to deployment, European Commission (2011) 1–13.

[3] Office, Publications, Directive 2009/28/EC of the European Parliament and of the Council on the Promotion of the Use of Energy From Renewable Sources and Amending and Subsequently Repealing Directives 2001/77/EC and 2003/30/EC (2009) 1–47.

[4] Office, Publications, Communication From the Commission - Europe 2020 - a Strategy for Smart, Sustainable and Inclusive Growth (2010) 1–35.

[5] J. Elkington, Towards the Sustainable Corporation: Win-Win-Win Business Strategies for Sustainable Development, California Management Review 36 (2) (1994) 90–100. doi:10.2307/41165746.

[6] W. Norman, C. MacDonald, Getting to the Bottom of "Triple Bottom Line", Business Ethics Quarterly 14 (02) (2004) 243–262. doi:10.5840/beq200414211.

[7] Office, Publications, Communication From the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions a Policy Framework for Climate and Energy in the Period From 2020 to 2030 (2014) 1–18.

[8] Energy Consumption Statistics, Odyssee (Apr. 2015).
URL http://www.odyssee-mure.eu

[9] S. Heinen, D. Elzinga, S.-K. Kim, Y. Ikeda, Impact of Smart Grid Technologies on Peak Load to 2050, International Energy Agency (2011) 1–44.

[10] M. V. Moreno, M. A. Zamora, A. F. Skarmeta, User-centric smart buildings for energy sustainable smart cities, Transactions on Emerging Telecommunications Technologies 25 (1) (2013) 41–55. doi:10.1002/ett.2771.

[11] S. M. Krause, S. Börries, S. Bornholdt, Econophysics of adaptive power markets: When a market does not dampen fluctuations but amplifies them, Physical Review E 92 (1) (2015) 012815. doi:10.1103/PhysRevE.92.012815.

[12] S. S. van Dam, C. A. Bakker, J. C. Buiter, Do home energy management systems make sense? Assessing their overall lifecycle impact, Energy Policy 63 (C) (2013) 398–407. doi:10.1016/j.enpol.2013.09.041.

[13] L. G. Swan, V. I. Ugursal, Modeling of end-use energy consumption in the residential sector: A review of modeling techniques, Renewable and Sustainable Energy Reviews 13 (8) (2009) 1819–1835. doi:10.1016/j.rser.2008.09.033.

[14] A. Capasso, W. Grattieri, R. Lamedica, A. Prudenxi, A Bottom-Up Approach to Residential Load Modeling, IEEE Transactions on Power Systems 9 (2) (1994) 957–964. doi:10.1109/59.317650.

[15] T. Räsänen, D. Voukantsis, H. Niska, K. Karatzas, M. Kolehmainen, Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data, Applied Energy 87 (11) (2010) 3538–3545. doi:10.1016/j.apenergy.2010.05.015.

[16] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegard, E. Wäckelgård, Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation, Energy & Buildings 41 (7) (2009) 753–768. doi:10.1016/j.enbuild.2009.02.013.

[17] M. Aydinalp, V. I. Ugursal, A. S. Fung, Modeling of the appliance, lighting, and space- cooling energy consumptions in the residential sector using neural networks, Applied Energy 71 (2001) 87–110.

[18] M. M. Armstrong, M. C. Swinton, H. Ribberink, I. Beausoleil-Morrison, J. Millette, Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing, Journal of Building Performance Simulation 2 (1) (2009) 15–30. doi:10.1080/19401490802706653.

[19] S. Gottwalt, W. Ketter, C. Block, J. Collins, C. Weinhardt, Demand side management—A simulation of household behavior under variable prices, Energy Policy 39 (12) (2011) 8163–8174. doi:10.1016/j.enpol.2011.10.016.

[20] J. Munkhammar, J. D. K. Bishop, J. J. Sarralde, W. Tian, R. Choudhary, Household electricity use, electric vehicle home-charging and distributed photovoltaic power production in the city of Westminster, Energy & Buildings 86 (2015) 439–448. doi:10.1016/j.enbuild.2014.10.006.

[21] J. V. Paatero, P. D. Lund, A model for generating household electricity load profiles, International Journal of Energy Research 30 (5) (2006) 273–290. doi:10.1002/er.1136.

[22] D. P. Jenkins, S. Patidar, S. A. Simpson, Synthesising electrical demand profiles for UK dwellings, Energy & Buildings 76 (2014) 605–614. doi:10.1016/j.enbuild.2014.03.012.

[23] M. Beaudin, H. Zareipour, Home energy management systems: A review of modelling and complexity, Renewable and Sustainable Energy Reviews 45 (C) (2015) 318–335. doi:10.1016/j.rser.2015.01.046.

[24] H. Hens, G. Verbeeck, B. Verdonck, Impact of energy efficiency measures on the CO_2 emissions in the residential sector, a large scale analysis, Energy & Buildings 33 (2001) 275–281.

[25] N. Pardo, C. Thiel, Evaluation of several measures to improve the energy efficiency and CO_2 emission in the European single-family houses, Energy & Buildings 49 (2012) 619–630. doi:10.1016/j.enbuild.2012.03.006.

[26] A. T. de Almeida, P. Fonseca, B. Schlomann, N. Feilberg, C. Ferreira, Residential monitoring to decrease energy use and carbon emissions in europe, in: EEDAL'06, 2006, pp. 1–17.

[27] V. A. Dakwale, R. V. Ralegaonkar, S. Mandavgane, Improving environmental performance of building through increased energy efficiency: A review, Sustainable Cities and Society 1 (4) (2011) 211–218. doi:10.1016/j.scs.2011.07.007.

[28] R. Huang, M. Itou, T. Tamura, J. Ma, Agents based Approach for Smart Eco-home Environments, in: The 2010 International Joint Conference on Neural Networks (IJCNN), 2010, pp. 1–8. doi:10.1109/IJCNN.2010.5596583.

[29] P. Stoll, N. Brandt, L. Nordström, Including dynamic CO_2 intensity with demand response, Energy Policy 65 (C) (2014) 490–500. doi:10.1016/j.enpol.2013.10.044.

[30] A. Nilsson, P. Stoll, N. Brandt, Assessing the impact of real-time price visualization on residential electricity consumption, costs, and carbon emissions, Resources, Conservation & Recycling (2015) 1–10doi:10.1016/j.resconrec.2015.10.007.

[31] M. Hart, R. de Dear, Weather sensitivity in household appliance energy end-use, Energy & Buildings 36 (2) (2004) 161–174. doi:10.1016/j.enbuild.2003.10.009.

[32] F. McLoughlin, A. Duffy, M. Conlon, Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study, Energy & Buildings 48 (2011) 240–248. doi:10.1016/j.enbuild.2012.01.037.

[33] M. Jalas, J. K. Juntunen, Energy intensive lifestyles: Time use, the activity patterns of consumers, and related energy demands in Finland, Ecological Economics 113 (C) (2015) 51–59. doi:10.1016/j.ecolecon.2015.02.016.

[34] REMODECE Survey Results for Norway, REMODECE Project, [Online; accessed 20-August-2015] (Feb. 2008).
URL http://www2.isr.uc.pt/~remodece/database/login.htm

[35] S. Faberi, M. Presutto, R. Stamminger, R. Scialdoni, W. Mebane, R. Esposito, Preparatory Studies for Eco-design Requirements of EuPs, Tech.

Rep. TREN/D1/40-2005 (Dec. 2007).

[36] J.-N. Louis, K. Leiviskä, E. Pongrácz, The Trade-Off Between Technology Deployment and Enviro-Economic Benefits in Smart Buildings, in: European Energy Market 2015, Lisbon, Portugal, 2015, pp. 1–5.

[37] Electricity contract for home and summer cottage (Sähkösopimus kotiin ja kesämökille), [Online; accessed 25-August-2015]. URL https://www.oulunenergia.fi/tuotteet-ja-palvelut/\sahkoa-kotiin/sahkosopimus-kotiin-ja-kesamokille

[38] S. Karjalainen, Consumer preferences for feedback on household electricity consumption, Energy & Buildings 43 (2-3) (2010) 458–467. doi:10.1016/j.enbuild.2010.10.010.

[39] R. K. Jain, R. Gulbinas, J. E. Taylor, P. J. Culligan, Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback, Energy & Buildings 66 (2013) 119–127. doi:10.1016/j.enbuild.2013.06.029.

[40] I. Ayres, S. Raseman, A. Shih, Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage, Journal of Law, Economics, and Organization 29 (5) (2013) 992–1022. doi:10.1093/jleo/ews020.

[41] C. B. A. Kobus, R. Mugge, J. P. L. Schoormans, Long-term influence of the design of energy management systems on lowering household energy consumption, International Journal of Sustainable Engineering 8 (3) (2015) 173–185. doi:10.1080/19397038.2014.991776.

[42] W. Abrahamse, L. Steg, C. Vlek, T. Rothengatter, The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents, Journal of Environmental Psychology 27 (4) (2007) 265–276. doi:10.1016/j.jenvp.2007.08.002.

[43] D. Bonino, F. Corno, L. De Russis, Home energy consumption feedback: A user survey, Energy & Buildings 47 (2012) 383–393. doi:10.1016/j.enbuild.2011.12.017.

[44] CEN, Functional reference architecture for communications in smart metering systems, TR 50572 (Dec. 2011).

[45] Office, Publications, Directive 2009/125/EC of the European Parliament and of the Council of 21 October 2009 establishing a framework for the setting of ecodesign requirements for energy-related products Text with EEA relevance (2009) 1–26.

[46] X. Feng, D. Yan, T. Hong, Simulation of occupancy in buildings, Energy & Buildings 87 (2015) 348–359. doi:10.1016/j.enbuild.2014.11.067.

[47] J.-N. Louis, A. Caló, K. Leiviskä, E. Pongrácz, A Methodology for Accounting the CO_2 Emissions of Electricity Generation in Finland, International Journal on Advances in Intelligent Systems 8 (3&4) (2014) 560–571.

[48] Statistics Finland, Household-dwelling units and housing population by housing density 1989-2014, Statistics Finland, [Online; accessed 20-August-2015] (Jun. 2015). URL http://www.stat.fi

[49] Statistics Finland, Household-dwelling units by number of persons and type of building 1985-2014, statistics Finland, [Online; accessed 20-August-2015] (Jun. 2015). URL http://www.stat.fi

[50] M. G. Ippolito, E. R. Sanseverino, G. Zizzo, Impact of building automation control systems and technical building management systems on the energy performance class of residential buildings: An Italian case study, Energy & Buildings 69 (2014) 33–40. doi:10.1016/j.enbuild.2013.10.025.

[51] J. Lynham, K. Nitta, T. Saijo, N. Tarui, Why does real-time information reduce energy consumption?, Energy Economics 54 (2015) 173–181. doi:10.1016/j.eneco.2015.11.007.