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DEVELOPING A STRATEGY FOR GENERATING ELECTRICAL LOAD

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Abstract

Electricity consumption data profiles that include details on the consumption can be generated with a bottom-up load models. In this paper the load is constructed from elementary load components that can be households or even their individual appliances. In this work a simplified bottom-up model is presented.

The model can be used to generate realistic domestic electricity consumption data on an hourly basis from a few up to thousands of households. The model uses input data that is available in public reports and statistics. Two measured data sets from block houses are also applied for statistical analysis, model training, and verification. Our analysis shows that the generated load profiles correlate well with real data.

Furthermore, three case studies with generated load data demonstrate some opportunities for appliance level demand side management (DSM). With a mild DSM scheme using cold loads, the daily peak loads can be reduced 7.2% in average. The modeling is based on a simplified approach where openly available data and statistics are used, i.e. data that is subject to privacy limitations, such as smart meter measurements are excluded.

KEY WORDS: bottom-up load model; house appliance; demand side management; electric load



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1. INTRODUCTION

Since the start of the industrial revolution the global energy-usage has increased with economic growth. Load data is crucial for planning electricity distribution networks and optimal production capacity. Accurate knowledge of the house consumer loads is important when small scale distributed energy technologies are optimally sized into the local network or local demand side management (DSM) measures are planned. This knowledge is also useful for planning medium and low voltage networks in residential areas.

The data that electric utilities typically have on domestic electricity consumption do not contain much information about its nature. The data is normally aggregated consumption of multiple buildings without knowledge about the events in individual houses. The fluctuation of electricity consumption concerning an individual building remains unrevealed as well as the division of consumption between different types of building appliances. Nevertheless, detailed knowledge can be produced with simulation models. The electricity demand models are often applied to forecast the demand at the utility level.

Rigorous studies on the topic were conducted already in the 1970s and 1980s, resulting in a large number of forecasting methods as reported by Gross and Galina (1987). A more recent review and classification of the forecasting methods has been given by Alfares and Nazeeruddin (2002), where novel methods including fuzzy logic, genetic algorithms and neural networks (Hippert et al., 2001) have been included in addition to the conventional econometric models (Pindyck and Rubinfeld, 1997). These kinds of forecasting methods are commonly employed when there is little or no knowledge about the appliance stocks and other grass-root level consumer details (Zarnikau, 2003).

End-use models, an alternative to the conventional demand forecasting, represent a bottom- up demand modeling approach. The accuracy of these models depends very much on the availability of grass-root level consumption details. An ideal case would be when the stock of appliances and their usage patterns in buildings are known and details about the composition of the load



are valued, as in ‘Capasso model’ published by Capasso et al., (1994). On the other hand, a utility level bottom-up method presented by Willis (2002) provides much less details on the individual consumer level, although it shows more details than the typical electric demand forecasting scheme.

A typical limitation for detailed bottom-up methods is an extensive need of data about the consumers or their appliances and the households in general. Usually, some part of the data is not easily available. In the Capasso model (Capasso et al., 1994), detailed data is needed about consumer behaviour. In addition to the consumer behaviour, the Norwegian ERAD model (Larsen and Nesbakken, 2004) also requires very detailed information about the design of the house in which the building is located. On the other hand, Sanchez et al. (1998) applied in their bottom-up model to large databases with partly incomplete or missing data, therefore compromising the accuracy of their results. In our work the need for detailed data is bypassed by using a representative data sample and statistical averages. The random nature of consumption is generated by using stochastic processes and probability distribution functions as the consumption is generated. But then, appliance ownership and daily usage pattern is determined in a similar manner to the Capasso model. As a result, our work demonstrates that quite detailed and realistic electricity consumption data can be generated using generally available appliance information and consumer statistics. The resulting loss in accuracy is compensated by considerable reduction in the data requirements. The purpose of this work is to demonstrate an easy-to-use consumer load data model that can be used to generate representative electricity consumption data. The method allows combination of individual household data sets into realistic large scale data including thousands of buildings. The model is finally verified with real electricity consumption data.

2. MODEL OF END-USER BEHAVIOUR AND APPLIANCE USAGE

The electricity consumption from appliances is mainly affected by: (a) the available setup of appliances in the building, (b) the load parameters of these, and (c) the actual usage of the appliances. A comprehensive set of domestic consumption data was analyzed in order to understand the fundamental characteristics of building load curves. The data was found to behave periodically on a seasonal, daily and hourly scale as discovered in previous Finnish load research projects (Seppälä, 1996; SLY, 1995) and in European



end-use measurement campaigns (Sidler, 1996, 2002). Convergence of the mean data with increasing number of households was also observed as suggested by Willis (2002). In addition, the distribution of the daily mean energy use was revealed after having removed the seasonal cyclic behaviour from the data.

2.1 PRE-PROCESSING

The domestic consumption data used for prevailing observations composed of two Finnish sets of data. The first set (data set 1) consisted of hourly data from a total of 702 households during the 365 days in the year 2012. The second set (data set 2) consists of hourly data from totally 1082 households during 143 days from September 2012 to January 2013, including also the households in the first data set during that period. The data set 2 is applied only in the analysis of the coincidental nature of the data, providing the increased number of households for better statistics. The data sets are composed of electricity measurements of complete blocks of flats excluding the electricity consumption not directly used inside the apartments. The blocks have between 27 and 74 apartments whose data consisted mainly of appliances and lighting.

Heavy electric heating loads such as space heating or cooling, water boilers or individual saunas were absent.

The daily electricity consumption on a yearly level is often dependent on external variables such as the mean outside temperature and daily daylight hours that typically follow similar patterns over successive years. Due to the northern location this shape becomes often sinusoidal for Finnish conditions (Haapakoski and Ruska, 1998; SLY, 1988). This is explained by the lack of summer time cooling loads, strong seasonal variation in the daylight hours and increased use of domestic appliances in the cold season (Haapakoski and Ruska, 1998). The daily electricity consumption in the first data set is shown in Figure 1(a) with a sinusoidal mean curve that models the seasonal variation. The hourly fluctuation of domestic loads results from the combined effect of consumer availability and activity level (Capasso et al., 1994). Thus the mean daytime consumption during workdays is typically lower than that in the weekends, and in the evening the consumption is somewhat higher compared to the weekend evenings. This is also observed in our data as presented in



Figure 1(b). The left side of the load curve presents the mean hourly consumption levels for an average weekday and the right side for the average weekend day. In the data sets, the mean daily consumption during weekdays is significantly lower than the weekend which is characteristic to Finnish load curves for blocks of flats (Adato, 1992).

At individual household level the electricity load curves vary much. The aggregated fluctuation smoothens out and approaches the mean consumption curve when the number of households included in the total load curve is increasing. The coincidental nature of the household loads and their smoothing has been discussed in detail by Willis (2002). In order to measure the smoothing effect for increasing amounts of household loads, an error sum $\sum |E_i - \bar{E}_i|$ was calculated over the hourly power demand data. In the sum 'E_i' is hourly power demand per household and \bar{E}_i is mean hourly power demand per household for all the households in the sample while I is index for the hours. Figure 1(c) shows, when using the log- log scale, how the error sum decreases almost linearly against the number of households using the data set 2 covering 143 days of data. The mean power demand was computed including all 1082 households in the data set.

Regardless of the number of similar household loads summed up, some variation remains in the mean daily energy consumption. The variation remains even when seasonal differences and differences between weekdays and weekend days have been compensated. This is partly due to a strong correlation between some loads and daily outside temperature fluctuations, such as heating or air conditioning (de Dear and Hart, 2002) that are not present in our load. It is also partly due to correlated social behaviour caused by such phenomena as local weather and local, national or international events. For example, television programs and commercial breaks in them can make variations observed in the national network. Such a level of details is not considered in our model, although the daily level of variation is included. As the mean seasonal variations are excluded from the daily mean data, only daily fluctuations from correlated social behaviour and uncorrelated random fluctuations remain. In our data sets long-term changes in mean temperature



has been included into the seasonal variations. As a result, temporal effects from short-term weather fluctuation effecting lighting and washing needs as well as entertainment use remain accompanied by the fluctuations caused by the social behaviour. Furthermore, a significant part of these

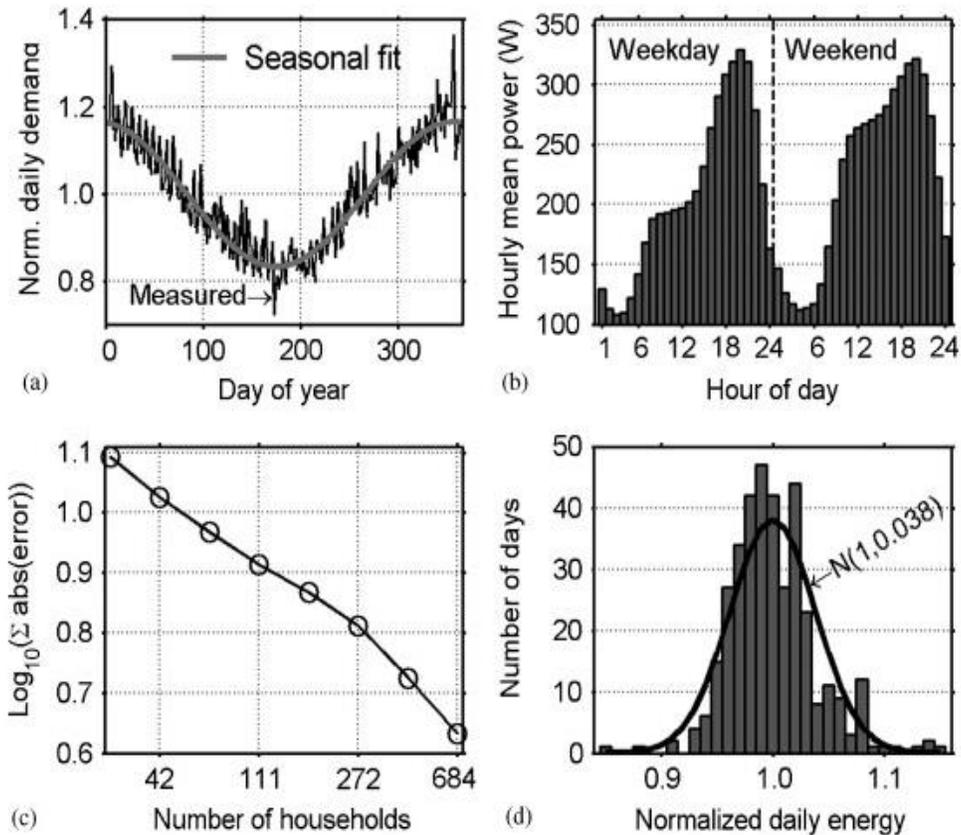


Figure1. (a) Daily electricity consumption of measured data set 1. The mean curve is presented by the line; (b) mean hourly consumption curve of a household for weekdays and weekend days for the data set 1; (c) effect of the number of households in the load data. The deviation is measured as absolute deviation from the normalized mean load; and (d) distribution of the measured mean daily electricity consumption for the first data set after seasonal and weekday compensation.



effects influence all local households simultaneously. We assume this to be the most significant cause of variations in the mean daily electricity consumption. These effects will typically appear regardless of the number of locally distributed households.

The distribution of the compensated mean daily electricity consumption of our data set 1 with 702 households is shown in Figure 1(d). There we have removed seasonal effects as well as the mean differences between weekdays and weekend days. The bell curve shown is a normally distributed density function. It can be concluded that the distribution of the compensated mean daily electricity consumption is approximately normal.

3. BOTTOM-UP SIMULATION MATHEMATICAL MODEL FOR ELECTRICITY CONSUMPTION

The consumer load models developed and presented in this journal are based on a bottom-up model methodology. Based on the observations above, we propose a two component bottom-up model for household electricity consumption. The structure of the model is given in Figure 2. The first part of the model (I) defines the general fluctuation of diurnal consumption levels and separate appliance stocks for each household. The second part (II) composes of the main procedures and simulates separately the use of each appliance in the each household. In general, any reference to ‘one appliance’ in the model can refer to an individual appliance or, a group of appliances in the household.

In the first part of the model the fluctuation of consumption levels is defined. This is achieved by determining the daily values of social random factor P_{social} . The best fitting probability density function and standard deviation for P_{social} are preferably defined from a data sample. An example of the distribution of daily energy consumption can be seen in Figure 1(d), which corresponds to the distribution of social random factor P_{social} . The daily values of social random factor are same to all of the modelled buildings.

The procedures in the first part of the model are repeated for all household appliances in each of the households. The sets of appliances used are defined statistically. Table I shows an example of the mean saturation levels for



selected appliances in all Finnish buildings (SF, 2003). The kind of statistical saturation levels are available for many countries, e.g. in the public statistics

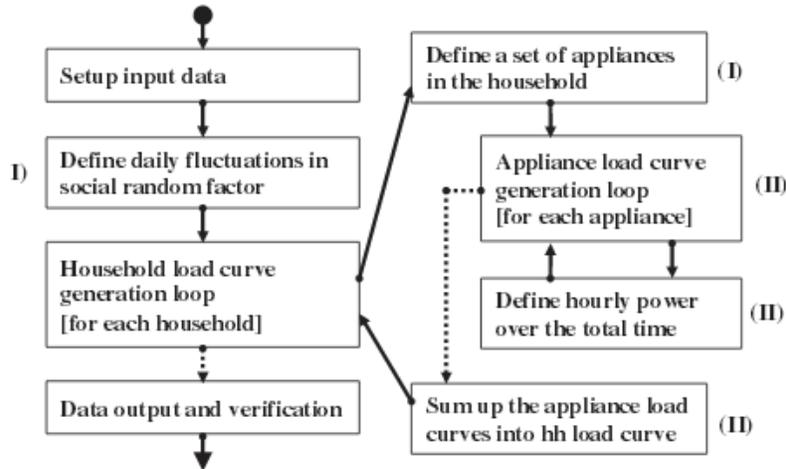


Figure2. Diagram for load generation procedure. The repeating structure is shown on the right. The point of entry to the procedure is marked with a large dot while the exit point is marked with a large arrow. The parts including computational loops have two exit arrows, one with solid line and one with dashed line.

The solid line points into the repeating loop itself and the dashed line points into the following step as the loop exits. The variable applied in the loop is explained in square brackets. Symbols (I) and (II) are showing the elements from the first and second part of the model, correspondingly.

Table I. Mean saturation levels for chosen appliances in all Finnish households (SF, 2003a).

Consumer durable	
%	
Colour TV	96
Satellite aerials	15
Videotape recorder	71
CD player	69
Personal computer	47



Freezer	87
Microwave oven	84
Washing machine	87
Dishwasher	50

references (Mansouri et al., 1996). When these saturation levels are applied as availability probabilities each household is defined with a unique set of appliances. This also makes the availability statistics to become coherent with the original one when a large number of households are considered.

The second part of the model (II) simulates the temporal electricity consumption profile of each individual appliance of each house separately. The electricity consumption of an appliance is based on its consumption cycle. On the other hand, the cycle is initiated based on its starting probability that is defined by the starting probability function P_{start}

$$P_{start}(A, W, \Delta t_{comp}, \sigma_{flat}, h, d) = P_{season}(A, W)P_{hour}(A, h, d)f(A, d)P_{step}(\Delta t_{comp})P_{social}(\sigma_{flat}) \quad 1$$

where P_{season} is the seasonal probability factor, models the seasonal changes, P_{hour} the hourly probability factor, models the activity levels during the day, P_{step} the step size scaling factor, scales the probabilities according to Δt_{comp} , P_{social} the social random factor, models the weather and social factors influencing the communal behaviour, f the mean daily starting frequency, models the mean frequency of use for an appliance ($1day^{-1}$), A the appliance or group of appliances, h the hour of the day, d the day of the week, W the week of the year, Δt_{comp} the computational time step (s or min), σ_{flat} the standard deviation for P_{social} . P_{start} is defined for each time step Δt_{comp} and it receives a value between 0 and 1. When the appliance is off, the turning on is checked using the probability P_{start} . Starting occurs when P_{start} is larger than a random number between 0 and 1. Then the consumption cycle of the appliance will be



added to its total load curve of the household. When the time of the on-cycle is reached ($t = t_{\text{start}} + t_{\text{cycle}}$) the appliance is turned off again and the checking for starting the appliance again will continue. For cumulative appliances, the starting checks will be done during the time the appliance is already on and simultaneously multiple similar appliances can be on (as for lighting). If an appliance has standby electricity use, it will be added to the whole load curve.

The input for the second part (II) of the model includes two kinds of parameters. Firstly, the weekly seasonal probability factors P_{season} together with the hourly probability factors P_{hour} for weekdays and weekend days constitute the probability factors in the model. Secondly, standby consumption and consumption cycle data with mean starting frequencies for each appliance form the constant parameters in the model. The weekly seasonal probability factor P_{season} is easiest to define from a measured data sample. The hourly probability factor P_{hour} is defined for each hour of a working day and a weekend day. This kind of data is quite readily available, but sometimes without separating between weekdays and weekend days (Ruska and Haapakoski, 1998; Sidler, 1996, 2002). The active and standby consumption parameters of an appliance are connected through their yearly energy consumption as below

$$E_{\text{yearly}} = \left(3600 \times 24 \frac{s}{\text{day}} \dot{E}_{\text{standby}} + f \sum_{n=1}^{n_{\text{cycle}}} \dot{E}_{\text{cycle},n} t_{\text{cycle},n} \right) \frac{365}{3.6 \times 10^6} \frac{\text{day kWh}}{\text{W s}}$$

Where E_{yearly} is the mean energy consumption per year (kWh), \dot{E}_{standby} the standby consumption level (W), $\dot{E}_{\text{cycle},n}$ the power level on step n of the mean consumption cycle (W), $t_{\text{cycle},n}$ the length of step n on the mean consumption cycle (s), n_{cycle} the number of steps on the mean consumption cycle.

If standby consumption level or the parameters for active consumption are known for an appliance, the mean energy consumption for the remaining part can be estimated by subtracting from the yearly energy E_{yearly} . Additionally,



the mean daily starting frequency f or total energy of the mean consumption cycle can be determined if one of them is defined.

Combining data from multiple sources may be needed to get reasonable estimates for both starting frequencies and consumption cycle parameters. These sources can include total yearly consumption with mean daily consumption profiles (Ruska and Haapakoski, 1998; Sidler, 1996, 2002) or just the yearly electricity consumption (Mansouri et al., 1996; Nutek, 1994; SLY, 1995).

Also typical power levels of household appliances are available, partly as they are crucial for some of the popular non-intrusive load monitoring methods (Cole and Albicki, 1998; Hart, 1992; Pihala, 1998; Rissanen, 1998; Sultanem, 1991; Wood and Newborough, 2003). The standby consumption levels are available at multiple sources (Meier et al., 2004; Rosen and Meier, 2000; Ross and Meier, 2002; Sidler, 1996, 2002).

Some calibration on the input values may be needed for good performance, which is typical with bottom-up models (Larsen and Nesbakken, 2004). In our case this is mostly due to the difference between the kind of households/appliances behind the input data and the kind of data the model is supposed to generate.

4. A GENERATED ELECTRIC LOAD PROFILE

Using the model described above, a large domestic electricity consumption data set has been generated applying the procedure in Figure 2. The data set composes of 100 households with consumption data for one full year for each individual household. The households are in blocks of flats with no heavy electric heating loads like space heater. The fractional household electricity consumption of different groups of appliances is based on an example in reference (Adato, 2004) and it is presented in Table II

Table II. An example about the division of electric consumption in a three person household living in a block apartment. Three rooms with 75m² total surface area have been assumed

Share of consumption	%
Cold appliances	24.6
Clothes-washer	7.0
Entertainment	17.5
Lighting	26.3



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Cooking	15.8
Total	100

Table BII. Hourly probability factors applied in the load model for appliances and groups.

Appliances		Hours																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
stove and oven	we	0.20	0.20	0.40	0.40	1.78	2.59	3.19	3.83	3.70	4.13	4.29	4.15	3.89	4.46	5.79	8.76	10.0	10.3	9.24	8.15	5.82	2.79	1.51	0.36
	wd	0.37	0.05	0.00	0.00	0.00	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.30	1.02
Microwave oven and coffee maker	we	0.20	0.20	0.40	0.40	1.78	2.59	3.19	3.83	3.70	4.13	4.29	4.15	3.89	4.46	5.79	8.76	10.0	10.3	9.24	8.15	5.82	2.79	1.51	0.36
	wd	0.37	0.05	0.00	0.00	0.00	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.30	1.02
Refrigerator and Freezers	we	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
	wd	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Clothes-washer and tumble dryer	we	1.73	0.96	0.40	0.40	0.40	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.80	8.60	8.16	7.01	5.05	2.03	
	wd	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.70	2.00	4.61	7.02	7.23	7.23	7.34	7.34	7.34	7.43	7.43	7.74	7.74	7.43	6.12	3.91	0.90
Televisions and video recorder	we	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
	wd	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
radio/player	we	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
	wd	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
personal computer and printer	we	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
	wd	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
Lighting	we	1.03	0.33	0.33	0.83	1.78	2.64	3.56	3.74	3.44	3.04	3.04	3.24	3.94	4.14	4.55	4.96	5.79	6.70	8.21	9.11	9.81	8.50	4.32	2.96
	wd	2.55	1.33	1.23	1.23	1.33	1.53	2.13	4.05	5.07	4.99	4.27	3.82	3.57	4.27	4.97	5.50	6.02	6.69	7.34	7.56	6.64	6.17	4.49	3.22
Other occasional Loads	we	1.03	0.83	0.83	0.83	1.03	2.04	3.06	3.24	3.44	3.54	3.64	3.74	3.94	4.14	4.55	4.96	5.79	6.70	7.71	8.51	9.01	8.10	5.67	3.66
	wd	2.55	1.33	1.23	1.23	1.33	1.73	2.13	3.55	4.07	3.99	3.77	3.97	4.07	4.47	4.97	6.00	6.32	6.84	7.34	7.56	6.79	6.67	4.84	3.22

We = weekend day; wd = weekdays

Table III. Applied saturation levels for appliances and groups.

Applied saturation (%)	
Appliances and groups	applied
Stove and oven	99
Microwave oven	84
Coffee maker	95
Refrigerator	99
Freezer	87
Second freezer	10
Dishwasher	50
Washing machine	43.5
Tumble dryer	6
Television	96
Second television	24
Video recorder	67
Radio/player	96
Personal computer	47
Printer	41
Lighting	100
Other occasional loads	100



The mean daily starting frequencies, the mean consumption cycle data and standby consumption for each appliance were defined simultaneously, as the values are interconnected. The values used here can be found at Table BII. The consumption cycles have been based on the report by Rissanen (1998), including the original appliance measurements prepared for the report (Private communication Oct. 2001 with Hannu Pihala, VTT, Finland). The standby rates have been compiled based on four references (Hirvonen and Tuhkanen, 2001; Pihala, 2001; Ross and Meier, 2002; Sidler, 1996). The daily starting frequencies have been defined based on the other parameters and the yearly consumption values estimated using references (Nutek, 1994; Sidler, 1996; SLY, 1995), the mean consumption in the targeted data and the fractions shown in Table II.

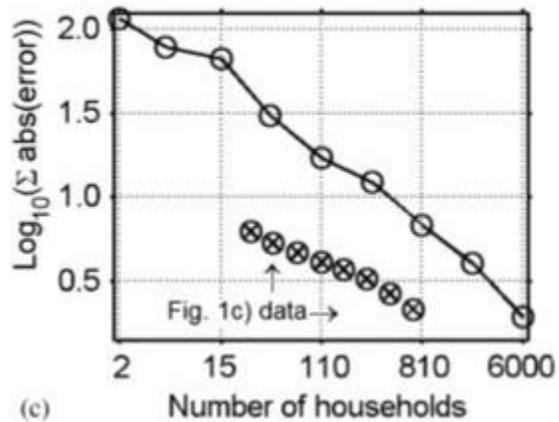
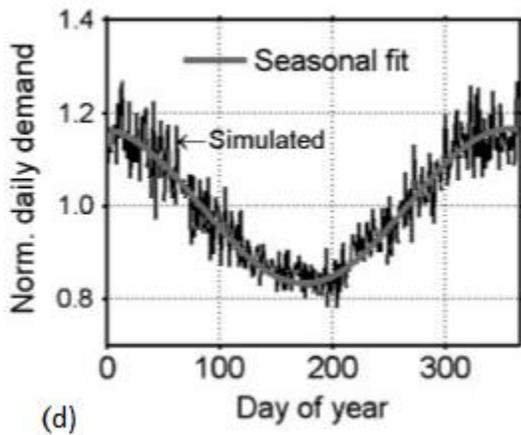
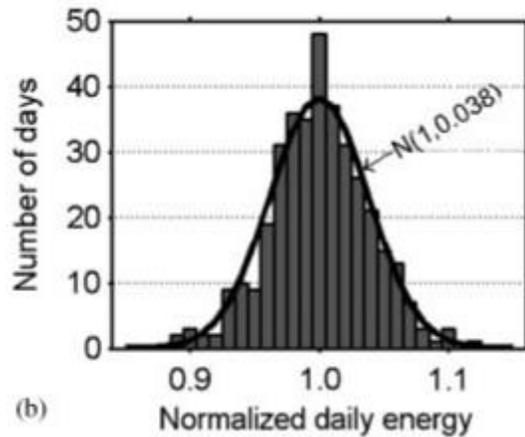
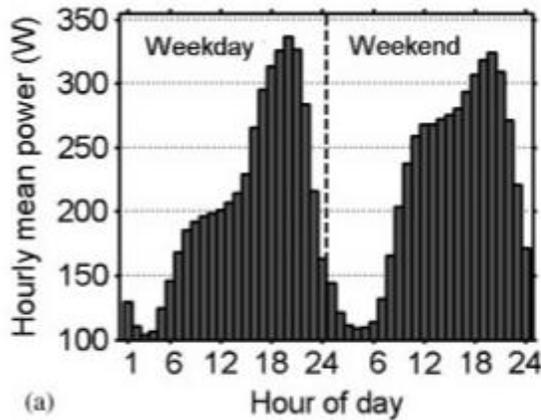




Figure 3; (a) mean hourly consumption curve of a household for weekdays and weekend days for the generated data set; (b) distribution of the compensated mean daily electricity consumption days for generated data set. The corresponding normally distributed curve is presented with thick dark line. (c) Coincidental behavior for generated data set. The corresponding data from Figure 1(c) is shown with symbol (d) Daily electricity consumption for generated data set. The mean curve from Figure 1 is presented with thick grey line

In the following, the simulated load is presented using the results from the measured data in Section 2 as goal values. The simulated daily energy consumption values are presented in Figure 3(d) together with the seasonal fit from the original measured data. The mean energy per day per household for the generated data is 5.16kWh day^{-1} , slightly higher than the 5.12kWh day^{-1} for the original data. When the seasonal effects and the differences in the weekends and weekdays are eliminated the statistical distribution of the data can be evaluated. Figure 3(b) shows the corresponding normal distribution. The standard deviation at the generated data after compensation is 0.203kWh day^{-1} and 0.196kWh day^{-1} for the original data, respectively.

The mean daily profiles resulting for the generated data are shown in Figure 3(a). The similarity of the generated and original data is demonstrated in when the Figures 1(a) and 3(a) are compared. Their hourly differences are below 3%, with an exception of 5% during some night hours. The coincidental nature of the simulated data is demonstrated in Figure 3(c). The absolute deviation of the data when increasing the number of unit loads in the total load from $n=1$ to $n=1000$ behaves as in Figure 1(c) for the measured data. For the simulated data, the magnitude of the errors is systematically higher. This is due to such nature of occupant behavior that is not captured by the model.

5. APPLICATION OF THE LOAD MODEL TO DSM

To demonstrate the usefulness of the bottom-up model, we present three DSM cases applying the 1000 household load data generated by the model in the previous sections. The household loads can be managed separately thus enabling DSM measures on an individual appliance level simultaneously in several households. Table II summarizes how the household load is divided between its major uses.



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Two kinds of DSM strategies are considered: shifting of the use to a later time, or, turning off the appliance. To keep the household operational some priorities need to be set up for the use of the appliances. The DSM strategies for the case studies are made following an assumed customer priority. Table IV summarizes the strategies for all the cases. Only 50% of lighting load in a household is allowed to be managed and the cold appliances can switch off for a maximum time of 1h a time with 1h recovery period in between. For simplicity, the management of appliances is done in groups as shown in Table IV.

In case 1 we consider a mild DSM to measure reduction of the peak load during weekdays throughout the year. By postponing the cold loads (priority 0 loads in Table II) during the peak consumption, reduction in actual peak loads and the mean peak load can be achieved. The second case applies a more complex overall DSM strategy to shave the highest consumption peak of the year. In this case the loads are regulated according to their priority order, and some compromises in the customer comfort are made. The last case demonstrates the full use of DSM to minimize the customer load in response to a sudden 3h black-out in early afternoon.

In case 1 the shift of the load of cold appliances by 1h results in a 7.2% reduction in the annual mean peak load. This result is achieved during weekdays without any noticeable inconvenience to the consumers. The resulting load curve during an average weekday is demonstrated in Figure 4, where also the original mean load curve can be seen. The peak reduction remains significantly smaller than the total cold-appliance capacity. This is due to the large number of peak load hours, causing only part of the cold appliances to be available for management simultaneously, as the cold loads are postponed only 1h at a time.



Table IV. The applied DSM strategies for appliances and groups in case studies 1–3

Appliances and groups	DSM strategies		
	Priority	Control	Limits
Stove and oven	1	cut	—
Microwave oven	1	cut	—
Coffee maker	1	cut	—
Refrigerator	0	post. 1 h	1 h
Freezer	0	post. 1 h	1 h
Second freezer	0	post. 1 h	1 h
Dishwasher	3	post. 6 h	—
Washing machine	2	post. 6 h	—
Tumble dryer	2	post. 6 h	—
Television	4	cut	—
Second television	4	cut	—
Video recorder	4	cut	—
Radio/player	4	cut	—
Personal computer	4	cut	—
Printer	4	cut	—
Lighting	5	cut	50%
Other occasional loads	5	cut	50%

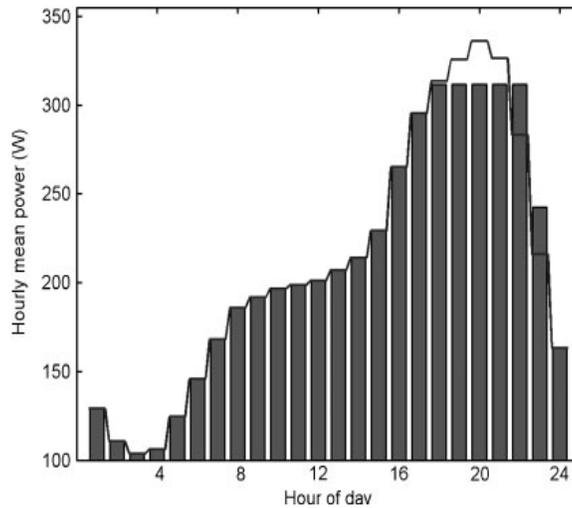


Figure 4. The mean demand curve for an average weekday after the DSM using the cold load for the management. Mean demand curves without DSM are presented with thick grey lines.

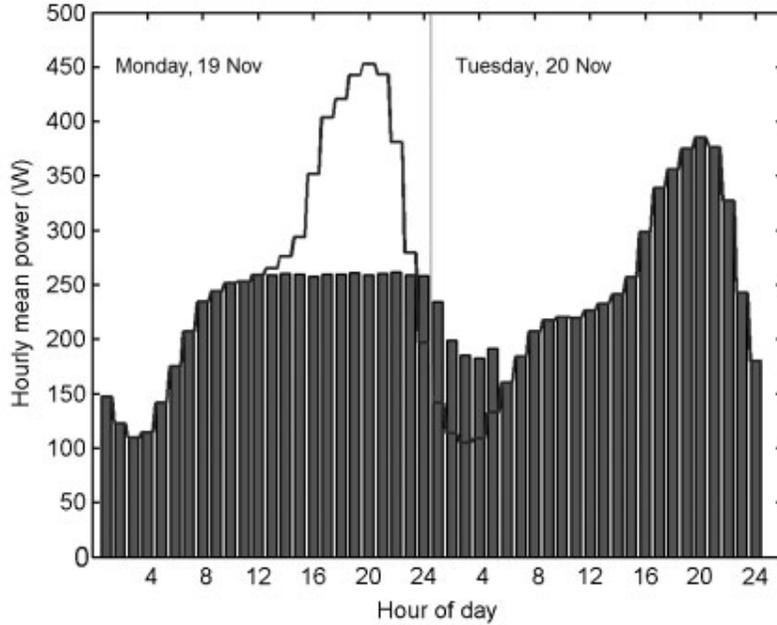


Figure 5. Peak demand day of the year and the following day after the DSM measures in case 2. The peak shaving has been only done during the peak conditions. Mean demand curves without DSM are presented with thick grey lines.

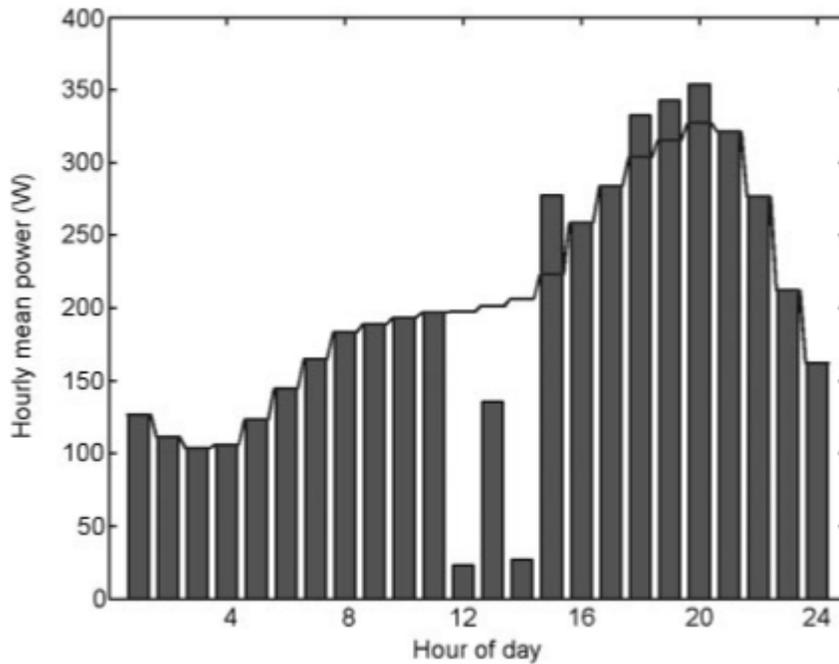




Figure 6. The resulting demand curve for the case 3 after the maximal DSM. The demand curve without DSM is presented with thick grey line. The second hour peak is due to postponed cold-appliance load during the first managed hour.

The result shown in Figure 4 is achieved as 3.1, 27.6, 52.9, 47.1, and 25.5% of the total cold load capacity is managed during the corresponding hours between 18 and 23. This way the postponed cold loads from the earlier hours can as well be smoothly managed.

In case 2, loads with priorities from 0 to 4 are controlled. Figure 5 shows the resulting total demand profile during the peak consumption day and during the following day. As a result, the peak value is reduced by 42%. This case violates the consumer comfort by postponing the washing loads between 14 and 23, by cutting the entertainment loads between 17 and 23 as well as by reducing the lighting use by 50% for 1h during the evening in 75% of the households. The postponed loads cause an increase of load between 23 and 5h in the off-peak period.

Figure 6 shows the resulting load profile in case 3, where measures in Table IV are fully utilized during the black-out. In this case, during the first hour a maximal load reduction is applied. The shifted cold-appliance load hits back on the second hour, while the third hour has again a full load reduction. As a result, the achieved mean load reduction is 61%. If the length of the black-out is known in the beginning of the load management, a smooth load response through stepped cold load monitoring can be achieved, as in case 1.

6. CONCLUSIONS

A realistic method for generating domestic electricity load profiles at individual household level has been presented. The model is based on a bottom-up approach in which the household load composes individual appliances or appliance groups. The input data of the model was mainly collected from public reports and statistics, although also the detailed appliance consumption data used in the work of Rissanen (1998) was applied. Additionally, two partly overlapping hourly domestic consumption data sets were applied for statistical analysis, model training, and verification.



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Consumption data with 1000 individual households has been generated with the suggested model. The verification applied to the data showed a good agreement between statistical qualities of the measured and the generated consumption data. The generated data has all individual consumption groups from Table II separately available for every individual household hourly throughout the year.

Three demand side management (DSM) case studies were done applying the separation of the generated consumption data into consumption groups at individual household level. First of the case studies demonstrates, that significant reduction of the daily peak consumption can be achieved by using DSM on the load of cold appliances. The load of cold appliances can partially be shifted off the peak hours without causing any customer inconvenience. The peak reduction could be improved further, if the freezers are available for extra cooling few hours before the peak period, using their thermal capacity this way as an extra storage. This would allow moving of the peak load also before the peak.

The second and third case studies were for an individual control need only. In the second case the highest consumption peak in the generated data was leveled using severe DSM causing inconvenience for the consumers. The third case was similarly a full DSM response to a sudden 3h loss of power. Significant consumption still remained in the third case due to the cold loads, requiring quite much reserve capacity to take care of it.

The household consumption data generating model could be employed also for different applications. But in industrial use, for example, the gathering of input data might require more effort, as the consumption of industrial equipment is less standard. In our future work, the model will be employed for studies of distributed energy generation systems.



REFERENCES

- Adato. 1992. Topographies of User Groups (ASCII). Adato Energia Oy: Helsinki, Finland; 4 floppy discs.
- Adato. 2004. Homely comfort with less energy } energy guide for every home. Adato Energia Oy 6010. Adato Energia Oy: Helsinki, Finland (in Finnish).
- Alfares HK, Nazeeruddin M. 2002. Electric load forecasting: literature survey and classification of methods. *International Journal of Systems Science* 33(1):23-34.
- Bunn DW, Seigal JP. 1983. Television peaks in electricity demand. *Energy Economics* 5 (1):31-36. DOI:10.1016/01409883(83)90006-3.
- Capasso A, Grattieri W, Lamedica R, Prudenzi A. 1994. A bottom-up approach to residential load modeling. *IEEE Transactions on Power Systems* 9(2):957-964. DOI:10.1109/59.317650.
- Cole AI, Albicki A. 1998. Data extraction for effective non-intrusive identification of residential power loads. *IEEE Instrumentation and Measurement Technology Conference*, 18-21 May, St. Paul Minnesota, USA. IEEE; 812-815. DOI:10.1109/IMTC.1998.676838.
- Dear R, Hart M. 2002. Appliance Electricity End-Use: Weather and Climate Sensitivity. Sustainable Energy Group, Australian Greenhouse Office: Canberra, Australia. FSO. 2004. Household Budget Surveys and Time Use. Federal Statistical Office: Germany. <http://www.destatis.de/themen/d/thmhaushalt.php>. 11/2/2004: 1 (in German).
- Gross G, Galiana FD. 1987. Short-term load forecasting. *Proceedings of the IEEE* 75 (12):1558-1573.
- Haapakoski M, Ruska T. 1998. Energy consumption of single-family houses with electric heating, demonstration project summary report II. Tutkimusraportteja IVO-A 04/98. Imatran Voima Oy, IVO Technology Centre: Vantaa, Finland (in Finnish).
- Hart G. 1992. Nonintrusive appliance load monitoring. *Proceedings of the IEEE* 80 (12):1870-1891.
- Hippert HS, Pedreira CE, Souza RC. 2001. Neural networks for short-term load forecasting: a review and evaluation. *IEEE Transactions on Power Systems* 16(1):44-55. DOI:10.1109/59.910780.
- Hirvonen R, Tuhkanen S. 2001. Basic metal and chemical industries, households and services. In *Energy Visions 2030 for Finland*, Kara M, Hirvonen R, Mattila Let al. (eds). VTT Energy: Helsinki, Finland; 157-175.
- Larsen BM, Nesbakken R. 2004. Household electricity end-use consumption: results from econometric and engineering models. *Energy Economics* 26 (2):179-200. DOI:10.1016/j.eneco.2004.02.001.
- Männistö S, Ovaskainen M-L, Valsta L (eds). 2003. The national FINDIET 2002 study. Publications of the National Public Health Institute B 3/2003. Kansanterveyslaitos: Helsinki, Finland; 130.



DSPG 2.0007/dspgjournal 07/2017

Delta State Polytechnic Ogwashi-uku Journal

www.dspgjournal.com ISSN: 2545 5222

- Mansouri I, Newborough M, Probert D. 1996. Energy consumption in UK households: impact of domestic electrical appliances. *Applied Energy* 54 (3):211–285. DOI:10.1016/0306-2619(96)00001-3.
- Meier A, Lin J, Liu J, Li T. 2004. Standby power use in Chinese homes. *Energy and Buildings* 36 (12):1211–1216. DOI:10.1016/j.enbuild.2003.10.011.
- Nutek. 1994. Household appliances in small houses. *Nutek B* 1994:11. Nutek: Stockholm, Sweden; 132 (in Swedish).
- Pihala H. 1998. Non-intrusive appliance load monitoring system based on a modern kWh-meter. VTT Publications, vol. 356. VTT: Espoo, Finland; 66. Pihala H. 2001. Measuring the electricity consumption of housing corporation on the free electricity market. TESLA- Report 47/2001 . VTT Energy: Espoo, Finland; 57 (in Finnish).
- Pindyck RS, Rubinfeld DL. 1997. *Econometric Models and Economic Forecasts* (4th edn). Irwin/McGraw-Hill: Boston, MA; 634.
- Rissanen J-P. 1998. Modeling of Electrical Appliances Based on the Profiles of their Real and Reactive Power Consumption. Helsinki University of Technology, Laboratory of Power Systems and High Voltage Engineering: Espoo, Finland (in Finnish).
- Rosen K, Meier A. 2000. Power measurements and national energy consumption of televisions and videocassette recorders in the USA. *Energy* 25 (3):219–232. DOI:10.1016/S0360-5442(99)00069-9.
- Ross JP, Meier A. 2002. Measurements of whole-house standby power consumption in California homes. *Energy* 27 (9):861–868. DOI:10.1016/S0360-5442(02)00023-3.
- Ruska T, Haapakoski M. 1998. Energy consumption of single-family houses with electric heating, demonstration project summary report III. *Tutkimusraportteja IVO-A* 04/98. Imatran Voima Oy, IVO Technology Centre: Vantaa, Finland (in Finnish).
- Sanchez MC, Koomey JG, Moezzi MM, Meier A, Huber W. 1998. Miscellaneous electricity in US homes: historical decomposition and future trends. *Energy Policy* 26 (8):585–593. DOI:10.1016/S0301-4215(98)00015-9. Seppälä A. 1996. Load research and load estimation in electricity distribution. VTT Publications, vol. 289. VTT: Espoo; 137. SF. 1998. Archive table ‘income and wealth of households by disposable income and type of building 1998, Finnish marks per household’. *Wealth Survey in Finland 1998*. Statistics Finland: Finland; Available only upon request. SF. 2001a. Archive table ‘ownership of consumer durables in households in Finland 2001’. *Household Consumption Expenditure Survey in Finland 2001*. Statistics Finland: Finland; Available only upon request. Copyright# 2005 John Wiley & Sons, Ltd. *Int. J. Energy Res* . 2006;30:273290
- Sidler O. 1996. Demand-side management: end-use metering campaign in the residential sector. *SAVE Programme Final Report*. Commission of the European Community: France.
- Sidler O. 2002. Demand side management. End-use metering campaign in 400 households of the European Community. *SAVE Programme, Project EURECO*. Commission of the European Communities: France.



DSPG 2.0007/dspgjournal 07/2017

Delta State Polytechnic Ogwashi-uku Journal

www.dspgjournal.com ISSN: 2545 5222

- Sidler O. 2003. DSM: major findings of an end-use metering campaign in 400 households of four European Countries. Proceedings of the 2003 ECEEE Summer Study: Time to Turn Down Energy Demand, 2–7 June 2003, Saint-Raphaël, France. The European Council for an Energy-Efficient Economy: France.
- SLY. 1988. Electricity use load measurement. *Julkaisuja* 3/88. Suomen sähkölaitosyhdistys ry: Helsinki, Finland; 110.
- SLY. 1995. Household electricity consumption survey 1993. *Julkaisusarja* 1995:1086. Suomen sähkölaitosyhdistys ry: Helsinki, Finland (in Finnish).
- SS. 2002. Indicators of material assets 1975–2001. Statistics Sweden: Sweden. <http://www.scb.se/templates/tableOrChart47918.asp>. 11/2/2004: 1 (in Swedish).
- Sultanem F. 1991. Using appliance signatures for monitoring residential loads at meter panel level. *IEEE Transactions on Power Delivery* 6(4):1380–1385. DOI:10.1109/61.97667.
- Willis HL. 2002. *Spatial Electric Load Forecasting* (2nd edn), Revised and Expanded. Marcel Dekker Inc.: New York, NY, USA; 766.
- Wood G, Newborough M. 2003. Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design. *Energy and Buildings* 35(8):821–841. DOI:10.1016/S0378-7788(02)00241-4.
- Zarnikau J. 2003. Functional forms in energy demand modeling. *Energy Economics* 25(6):603–613.