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A model for generating household electricity load profiles

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SUMMARY

Electricity consumption data profiles that include details on the consumption can be generated with a bottom-up load models. In these models 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. With more severe DSM schemes the peak load at the yearly peak day can be completely levelled with 42% peak reduction and sudden 3 h loss of load can be compensated with 61% mean load reduction. Copyright © 2005 John Wiley & Sons, Ltd.

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

1. INTRODUCTION

Load data is crucial for planning electricity distribution networks and optimal production capacity. Accurate knowledge of the household 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 households without knowledge about the events in individual households. The fluctuation of electricity consumption concerning an individual household remains unrevealed as well as the division of consumption between different types of household appliances. Nevertheless, detailed knowledge can be produced with simulation models.

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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 modelling 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 households 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 ERÅD model (Larsen and Nesbakken, 2004) also requires very detailed information about the design of the house in which the household 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 households. The model is finally verified with real electricity consumption data.

2. OBSERVATIONS AND HYPOTHESIS ON THE BEHAVIOUR OF HOUSEHOLD ELECTRICITY CONSUMPTION DATA

A comprehensive set of domestic consumption data was analysed in order to understand the fundamental characteristics of household 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.

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 2002. The second set (data set 2) consists of hourly data from totally 1082 households during 143 days from September 2002 to January 2003, 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 $\sum |\dot{E}_i - \bar{\dot{E}}_i|$ was calculated over the hourly power demand data. In the sum $\dot{E}_i$ is hourly power demand per household and $\bar{\dot{E}}_i$ 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,

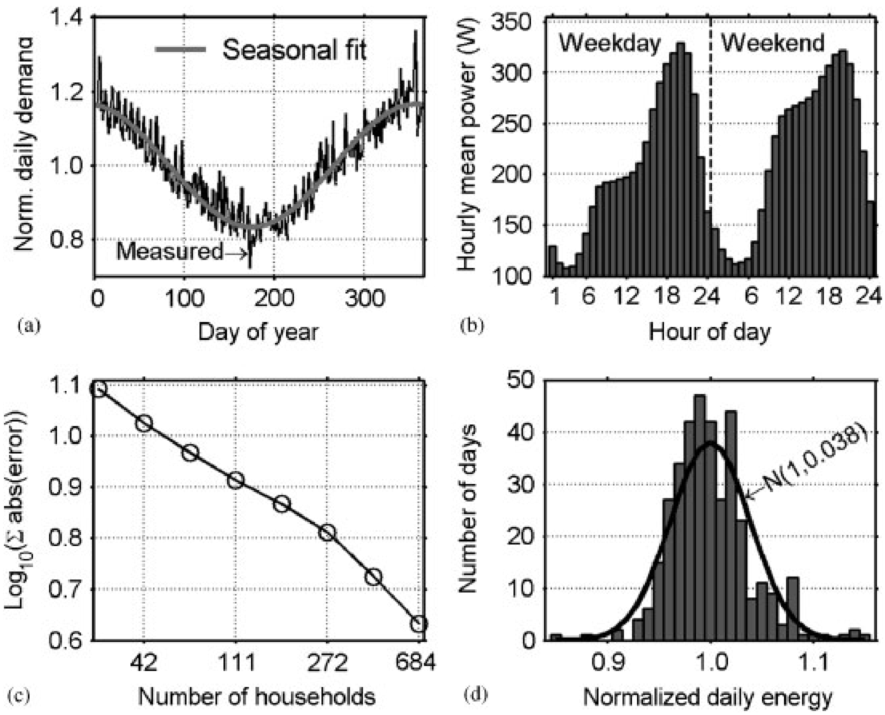

Figure 1. (a) Daily electricity consumption of measured data set 1. The mean curve is presented by the line; (b) mean hourly consumption curve of a household for weekdays and weekend days for the data set 1; (c) effect of the number of households in the load data. The deviation is measured as absolute 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.

national or international events. For example, television programs and commercial breaks in them can make variations observed in the national network (Bunn and Seigal, 1983). 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 effects influences 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. MATHEMATICAL MODEL FOR HOUSEHOLD ELECTRICITY CONSUMPTION

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 diurnal 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 households.

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 households (SF, 2003). The kind of statistical saturation levels are available for many countries, e.g. in the public statistics

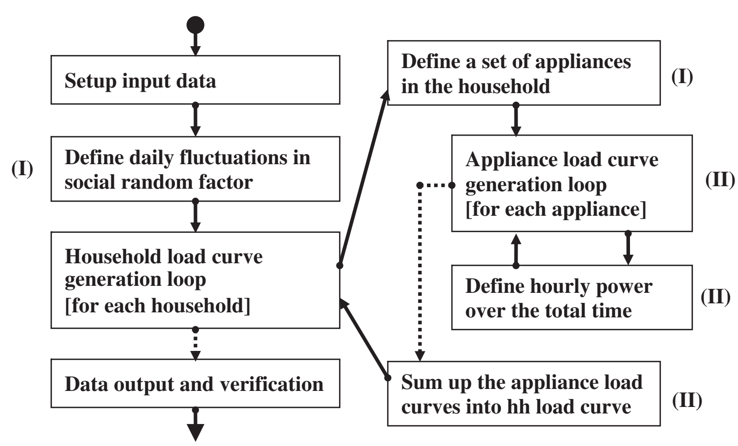

Figure 2. Diagram for load generation procedure. The repeating structure is shown on the right. The point of entry to the procedure is marked with a large dot while the exit point is marked with a large arrow. The parts including computational loops have two exit arrows, one with solid line and one with 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 durables	%
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

of references (Mansouri *et al.*, 1996; SF, 2003; SS, 2002; FSO, 2004). 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 household 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}.

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

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 ($1\,\text{day}^{-1}$), 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. Some additional computational characteristics for parameters of starting probability function P_{start} are shown in Appendix A.

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.

$$E_{\text{yearly}} = \left(3600 \times 24\,\frac{s}{\text{day}}\,\dot{E}_{\text{standby}} + f\sum_{n=1}^{n_{\text{cycle}}} \dot{E}_{\text{cycle},n}\, t_{\text{cycle},n}\right)\frac{365}{3.6 \times 10^{6}}\;\frac{\text{day kWh}}{\text{W}\,s} \tag{2}$$

where E_{yearly} is the mean energy consumption per year (kWh), $\dot{E}_{\text{standby}}$ 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 $\dot{E}_{\text{yearly}}$. 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 WITH VERIFICATION

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 10 000 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 heating. 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.

The appliance saturation data was mostly obtained from Statistics Finland (SF 2001a,b, 2003) while the coffee maker saturation was compiled from different sources (Männistö *et al.*, 2003) (Private comm. 20th November 2004 with Päivi Suomalainen, Market Research Manager,

Table II. An example about the division of electric consumption in a three person household living in a block apartment. Three rooms with 75 m^2 total surface area have been assumed (Adato, 2004).

Share of consumption	%
Cold appliances	24.6
Clothes-washer	7.0
Dishwasher	8.8
Cooking	15.8
Entertainment	17.5
Lighting and misc.	26.3
Total	100.0

Table III. Applied saturation levels for appliances and groups. Column 'Orig.' has the original values available in the listed references, while column 'Applied' presents the corresponding availability probabilities applied in the load model.

	Appliance saturation (%)		
Appliances and groups	Applied	Source	Orig.
Stove and oven	99	A	96
Microwave oven	84	B	84
Coffee maker	95	E	95
Refrigerator	99	D	97
Freezer	87	B,D	87
Second freezer	10	D	20
Dishwasher	50	B,D	50
Washing machine	43.5	B,D	87
Tumble dryer	6	A	3-13
Television	96	B,C	96
Second television	24	D	48
Video recorder	67	B,D/C	71/77
Radio/player	96	B,D/C	69/75*
Personal computer	47	B,D/C	47/51
Printer	41	C	41
Lighting	100	—	—
Other occasional loads	100	—	—

Sources: A = SLY, 1995; B = SF, 2003; C = SF, 2001b; D = SF, 2001a; E = Männistö *et al*., 2003.
*The reference value for CD-players only.

Oy Gustav Paulig Ab, Finland). Slight modifications of the data were necessary, as the saturation data was not intended for the targeted household group only but for whole Finland. The original and modified saturation levels are presented in Table III. The main reasons for reducing the ownership densities is the lower than average income level of the people living in apartments in Finland (SF, 1998) together with the lower appliance densities in households with low income (SF, 2001c, 2002).

The yearly curve fitted to data set 1 is applied to define the weekly seasonal probability factors P_{season}. The hourly probability factors were fundamentally based on results in (Sidler, 1996, 2003). Reference (Ruska and Haapakoski, 1998) was applied to evaluate the difference in social behaviour as well as climate conditions. The distributions used for hourly probability factors can be found in Table BI in Appendix B. On the other hand, the values for P_{social} for the first part of the model were defined applying the normal distribution function and standard deviation of data set 2.

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 in Appendix B. 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

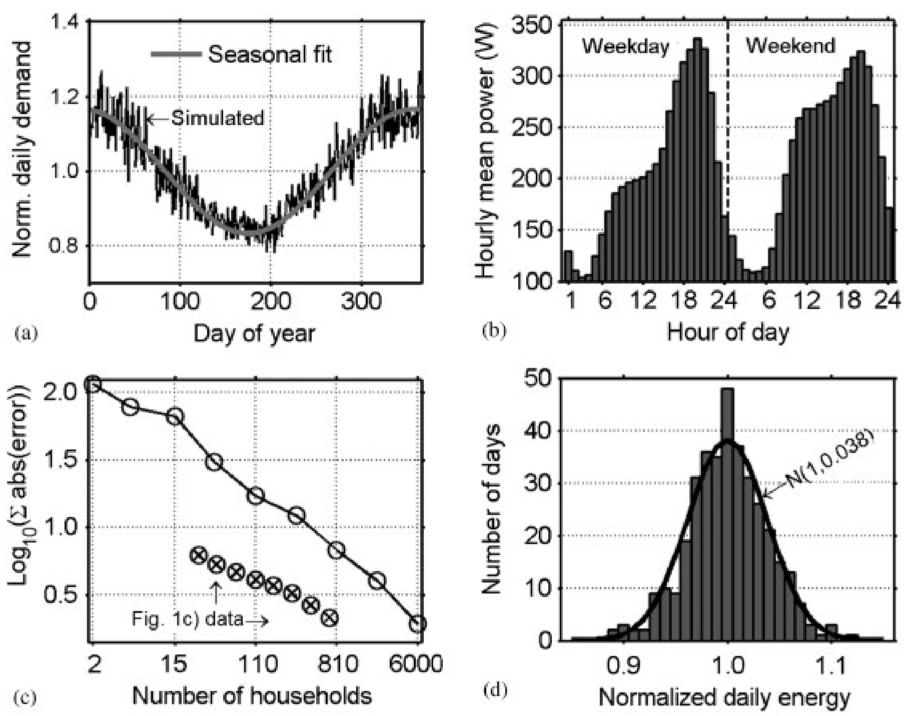

Figure 3. (a) Daily electricity consumption for generated data set. The mean curve from Figure 1 is presented with thick grey line; (b) mean hourly consumption curve of a household for weekdays and weekend days for the generated data set; (c) coincidental behaviour for generated data set. The corresponding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

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.

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(a) together with the seasonal fit from the original measured data. The mean energy per day per household for the generated data is 5.16 kWh day^{-1}, slightly higher than the 5.12 kWh 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(d) shows the corresponding normal distribution. The standard deviation at the generated data after compensation is 0.203 kWh day^{-1} and 0.196 kWh day^{-1} for the original data, respectively.

The mean daily profiles resulting for the generated data are shown in Figure 3(b). The similarity of the generated and original data is demonstrated in when the Figures 1(b) and 3(b) 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 behaviour 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 10 000 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.

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 1 h a time with 1 h 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 3 h black-out in early afternoon.

In case 1 the shift of the load of cold appliances by 1 h 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

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

	DSM strategies		
Appliances and groups	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%

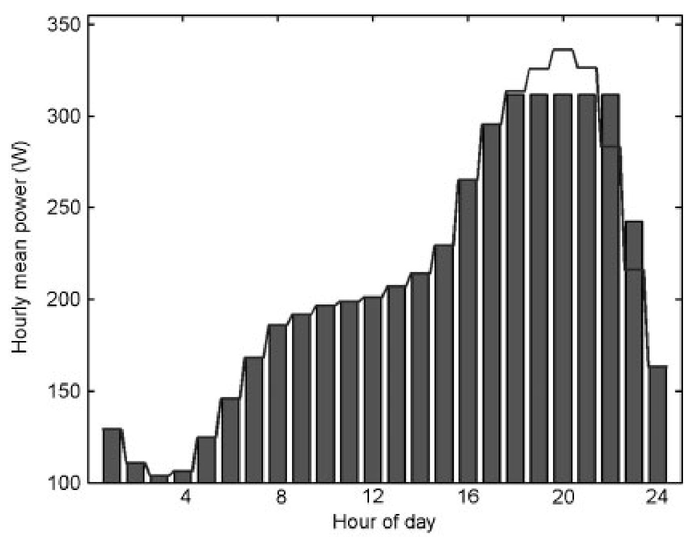

Figure 4. The mean demand curve for an average weekday after the DSM using the cold load for the management. Mean demand curves without DSM are presented with thick grey lines.

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

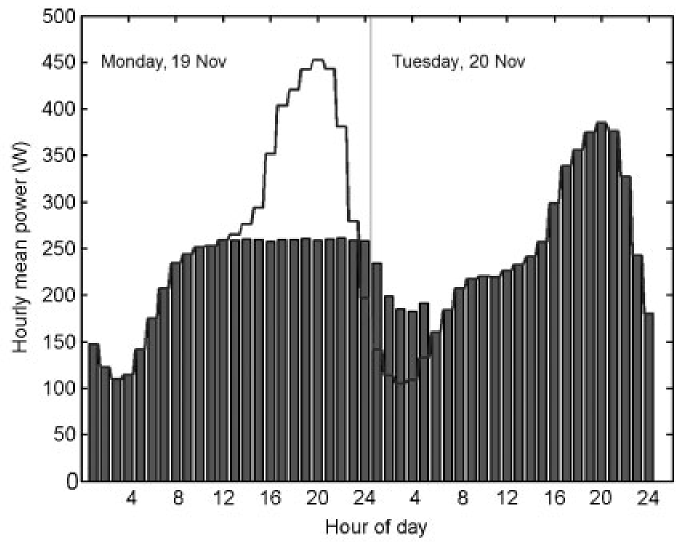

Figure 5. Peak demand day of the year and the following day after the DSM measures in case 2. The peak shaving has been only done during the peak conditions. Mean demand curves without DSM are presented with thick grey lines.

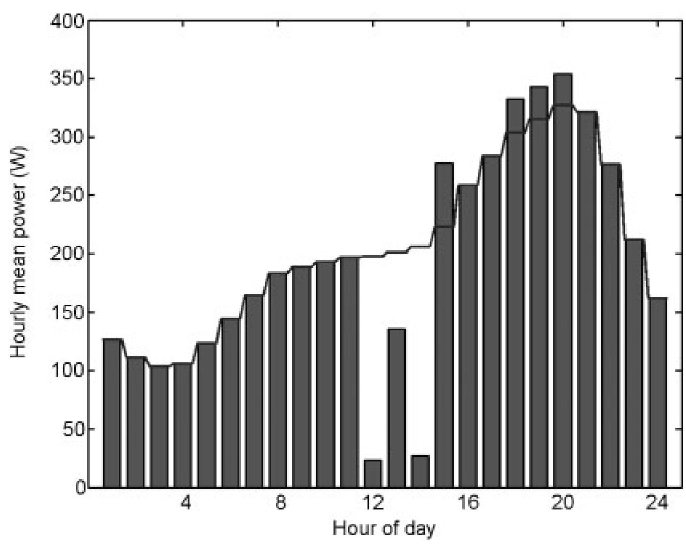

Figure 6. The resulting demand curve for the case 3 after the maximal DSM. The demand curve without DSM is presented with thick grey line. The second hour peak is due to postponed cold-appliance load during the first managed hour.

management simultaneously, as the cold loads are postponed only 1 h at a time. 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 1 h during the evening in 75% of the households. The postponed loads cause an increase of load between 23 and 5 h 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.

Consumption data with 10 000 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 levelled using severe DSM causing inconvenience for the consumers. The third case was similarly a full DSM response to a sudden 3 h 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.

NOMENCLATURE

A	= appliance or group of appliances
d	= day of the week
$\dot{E}_i$	= hourly power demand per household while i is index for the hours
$\bar{\dot{E}}_i$	= mean hourly power demand per household for all the households in a sample while i is index for the hours
E_{yearly}	= mean energy consumption per year (kWh)
$\dot{E}_{\text{standby}}$	= standby consumption level (W)
$\dot{E}_{\text{cycle},n}$	= power level on step n of the mean consumption cycle (W)
f	= mean daily starting frequency, models the mean frequency of use for an appliance ($1\,\text{day}^{-1}$)
h	= hour of the day
n_{cycle}	= number of steps on the mean consumption cycle
P_{season}	= seasonal probability factor, models the seasonal changes
P_{hour}	= hourly probability factor, models the activity levels during the day
P_{step}	= step size scaling factor, scales the probabilities according to Δt_{comp}
P_{social}	= social random factor, models the weather and social factors influencing the communal behaviour
$t_{\text{cycle},n}$	= length of step n on the mean consumption cycle (s)
t_{start}	= appliance starting time
W	= week of the year

Greek letters

Δt_{comp}	= computational time step (s or min)
σ_{flat}	= standard deviation for P_{social}

APPENDIX A

The probability factors in Equation (1) have the following additional characteristics:

$$N_{\text{steps}} P_{\text{step}} = 1.0 \quad \text{when } N_{\text{steps}} = \frac{\Delta t_{\text{comp}}}{60\,\text{min}}$$

$$\sum_{h=1}^{24} P_{\text{hour}}(A = A_n, h, d = d_m) = 1.0, \qquad \frac{\sum_{W=1}^{52} P_{\text{season}}(A, W)}{52} = 1.0$$

N_{steps} is the number of computational steps per hour while A_n and d_m represent any chosen appliance during any chosen day, correspondingly. As shown below, the mean yearly starting rate can be calculated as the sum over the daily starting frequencies.

$$N_{\text{year,mean}}(A) = \sum_{W=1}^{52} \sum_{d=1}^{7} \sum_{h=1}^{24} \sum_{\text{steps}} \langle P_{\text{appl}}(A, h, d, W, \Delta t_{\text{comp}}, \sigma_{\text{flat}}) \rangle$$

$$= \underbrace{\sum_{W=1}^{52} P_{\text{season}}(A, W)}_{=52} \sum_{d=1}^{7} f(A, d) \underbrace{\sum_{h=1}^{24} P_{\text{hour}}(A, h, d)}_{=1} \underbrace{\sum_{\text{steps}} P_{\text{step}}(\Delta t_{\text{comp}})}_{=1} \underbrace{\langle P_{\text{social}}(\sigma_{\text{flat}}) \rangle}_{=1}$$

$$\Leftrightarrow N_{\text{year,mean}}(A) = 52(5f(A, \text{weekday}) + 2f(A, \text{weekend day}))$$

APPENDIX B

Details of model input are presented in Tables BI and BII.

Table BI. Daily starting frequencies, standby loads and consumption cycle information applied in the load model for appliances and groups.

	Power (W) and time (min) cycles									Daily frequency		
Appliances and groups	P1	T1	P2	T2	P3	T3	P4	T4	Stand-by (W)	Weekday	Weekend	Other
Stove and oven	1050	12	525	18	220	12			0	0.56	0.61	C,G
	1100	12	550	6						0.70	0.76	C,G
	2100	24	700	6	1400	6	0	6		0.20	0.21	
Microwave oven	800	6							3	0.98	1.06	
Coffee maker	640	6	105	18						0.98	1.06	
Refrigerator	110	12	0	24						40.5	41.3	
Freezer	155	12	0	12						40.5	41.3	
Second freezer	190	12	0	12						40.5	41.3	
Dishwasher	1800	18	220	18	1800	6	220	12		1.16	1.26	
Clothes-washer	2150	12	210	24	450	6				0.31	0.33	
	2150	18	210	24	450	6				0.11	0.12	
Tumble dryer	2500	72								0.28	0.30	
Television	105	60							8	1.95	2.12	
Second television	75	60							4	0.28	0.30	
Video recorder	—	—							9	—	—	
Radio/player	30	60							5	4.18	4.54	
Personal computer	125	60							3	0.70	0.76	
Printer	30	60							4	0.14	0.15	
Lighting	120	30								18.0	19.5	C,G
Other occasional loads	1000	30							3	0.14	0.15	G

P# = power in Watts for cycle #; T# = time in minutes for cycle #; C = cumulative use allowed; G = represents a group of appliances.

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

Appliances		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
		Hours																							
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
Dishwasher	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	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
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	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 = weekday.

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