"ENERGY PATTERN GENERATOR" – UNDERSTANDING THE EFFECT OF USER BEHAVIOUR ON ENERGY SYSTEMS

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Abstract

To understand and research the effect of user behaviour on energy performance, an Energy Pattern Generator (EPG) is being developed. This software tool produces high resolution electricity and heat demand patterns for five different household types. In addition, energy consumption is related to five common types of dwellings in the Netherlands. Input for the EPG is provided by measured energy demand profiles of common household appliances and statistical data from time-of-use surveys.

Internal heat gains due to appliances play an important role in the energy balance of energy efficient buildings. These gains are however often simplified in today's tools into (at best) fixed weekly schedules. The EPG provides a more realistic representation of (the variation in) occupant behaviour. Varying internal gains are calculated for several user profiles, based on variations in the use of domestic appliances and the household occupancy by the residents. Using the EPG as a "plug-in", building simulation can determine whether new building concepts are 'user proof'.

The EPG is also of importance in the design of (intelligent) electricity grids as it provides dynamics in the grid's loads. The EPG provides insight in actual loads which can be scaled up to i.e. district level.

Key words: Building Future, Innovative Building Concepts; Energy Pattern Generator (EPG); User Behaviour; Household Profiles; Energy Consumption.

1. Introduction

In the Netherlands the market pull for energy efficient building concepts is growing. ECN, TNO and OTB have joined forces in a research program, called Building Future, to develop innovative building concepts. Building Future has high ambitions with regards to energy performance and aims for an energy neutral built environment around 2050.

User behaviour has a significant impact on the energy performance of dwellings. For example, indoor temperature, lighting levels, use of appliances and shower behaviour all relate to energy consumption. Composition of household and occupancy makes this effect even more complex. In current development of building concepts, this variety in user behaviour is rarely and not structurally incorporated.

The need for addressing this user behaviour issue becomes more significant in case of development of ambitious, energy efficient building concepts. User behaviour will have a relatively larger impact on total energy consumption. Varieties in energy consumption will increase. This implies the need for more robust 'user proof' building concepts.

An important aspect of developing building concepts is modeling of energy demand on household level, as it provides insight in user behaviour related to energy consumption. However, current models are often applied to forecast the demand at utility level. Studies on this topic are already conducted since the 1970s and advanced models that can forecast the demand at high accuracy have been developed. These models rely on the principle of aggregation, where demand spikes at the individual level are cancelled out on higher level of aggregation. Models on an individual level, where the spiky behaviour is an important characteristic of the demand profile, are much harder to build, especially if one wants to obtain high resolution profiles.

In this article, an energy pattern generator (EPG) is described. This EPG is a software tool that creates patterns at a one minute resolution scale for electricity and gas consumption for a single household. Optionally it can also create electricity production patterns if the household has electricity generating devices like photovoltaics. Thus, the energy patterns resemble measurements from the electricity and gas meters in a building at a one minute resolution. Most appliances in a household can be modeled by statistics only. This means that at any moment there is a probability that the appliance will turn on or shut down. However, some appliances are used for time dependent processes, an example being space-heating. Because of the interaction between appliance and process (the house will heat up if the appliance is turned on, but the appliance turns on only if it the temperature in the house is below the set point) such appliances cannot be modeled by statistics alone. Therefore, the EPG has two main pattern generators; a statistical and a dynamical one, as is shown in Figure 1. The statistical pattern generator only models the appliances if their energy consumption can be described by statistics only. Similar, the dynamic pattern generator models appliances that interact with dynamic physical processes. These two pattern generators are supplemented with models for resident occupancy and domestic hot water. Furthermore, five different household profiles are defined as input for the statistical pattern generator, based on research on drivers for energy saving behaviour. Each household profile implicates a unique list of appliances present in the household, including their yearly energy consumption.

In this paper the development of household profiles is discussed first, introducing four drivers for energy saving behaviour. Next, the working principles of the statistical and dynamical pattern generator are explained. Finally, the output of the Energy Pattern Generator is analyzed, discussing preliminary results.

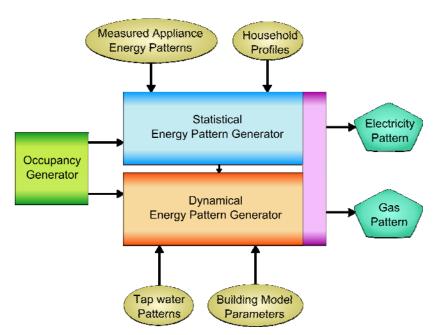


Figure 1: Schematic outline of the Energy Pattern Generator.

2. Household characteristics

Energy use in a home is determined by technical and architectural characteristics (home characteristics) on one hand, and behaviour of the residents (household characteristics) on the other hand. A particular attitude related to energy use may be an important determinant of behaviour. In the 80s, Raaij and Verhallen (1983a) determined energy-related attitudes as price concern, environmental concern, energy concern, health concern, and attitudes toward personal comfort. The researchers monitored 145 households in Vlaardingen (the Netherlands) from November 1976 to November 1977. The study focused on the behaviour of household members as a major determinant of household energy use. The authors stated that an attitude is related to behaviour, but does not necessarily cause behaviour. A household or family life-style influences energy-related attitudes and behaviour. Family size and composition next to the presence or absence from home for work or leisure all have a direct effect on energy behaviour and energy use. Household income, educational level, and employment showed also to be related to energy use (Raaij and Verhallen, 1983a).

More recent research by, for example, Poortinga et al (2003) and Vringer (2005) showed comparable results. The aim of the study of Poortinga et al (2003) was to examine the influence of characteristics of energy saving measures on acceptability, next to the relationships between preferences for different types of energy-saving measures and various socio-demographic variables, and environmental concerns of the respondents. A survey study was conducted during October and November 1999 in 455 randomly-selected households spread over the Netherlands. Poortinga et al (2003) found differences in acceptability of energy-saving strategy measures with regard to age, household type, income, and level of education. Vringer (2005) investigated different elements that potentially influence spending pattern and energy use, like total income, total spending, age of the main bread-winner, and the composition of the household. Results showed that income and composition of the household can have a significant influence on energy use. In an attempt to explain more of the variance, additional elements like value patterns, motivation to save energy, and interest in energy-related social issues were investigated. Motivation to save energy significantly explains difference in energy use. According to Vringer (2005), the least motivated group of people used approximately 4% more energy than averagely or highly motivated groups.

3. User profiles

In the study of Raaij and Verhallen (1983a), next to energy-related attitudes itself, also relationships between these attitudes, household behaviour, home characteristics, socio-demographics, and the actual use of natural gas for home heating were investigated. Based on four variables (home temperature during presence and during absence, airing rooms, and use of the hall door), energy use patterns were grouped into five major behavioural clusters (Raaij and Verhallen, 1983b):

- Conservers (low temperature as well as a low ventilation level)
- Spenders (a high score on at least three of the four variables)
- Cool (a low temperature but are average or high on ventilation)
- Warm (average or high temperatures and low ventilation)
- Average (average scores on both temperature and ventilation)

Since 1995 energy-saving interventions are mandatory to be implemented in Dutch homes, potentially changing energy use patterns and behaviour of households. Income, age of family members and the organization of the household were still significant predictors of energy use patterns. Interesting result of the study of Poortinga et al (2003) was that respondents who were contradictory in environmental concern differed in acceptability judgments of small and large energy-saving measures. Respondents with a high environmental concern found measures with small energy savings relatively more acceptable than measures with large energy savings, while the reverse applied to respondents with a low environmental concern. Environmental concern was also part of a study done in 2007 (Groot et al., 2008; TNO-ECN, 2007). In this study a field test to study current behavioural aspects was conducted in more than 80 participating Dutch households within the Building Future project. The investigated group was divided into five different types, based on family arrangement (e.g., single, couple, family). The household members were interviewed about

potential drivers for energy consuming and/or saving behaviour, e.g. saving money, saving the environment, or personal convenience. Based on this finding, four different energy user profiles were designed:

- Profile 'Convenience/Ease': people in this profile act because of comfort needs and have no interest in energy use, money, nor environment;
- Profile 'Conscious': these people choose for comfort, but are very aware of the consequences for the environment and their own financial situation;
- Profile 'Costs': people are very aware of the (energy) costs and consume as little energy as possible to save money;
- Profile 'Climate/Environment': these people act entirely because they care about the environment.

The four resulting profiles were not validated with existing data in the 2007 study, and the relation between the different profiles and electrical devices at home is not yet established. Data in Table 1 show that different household types have different drivers for energy saving behaviour. However, the costs aspect is important for all household types.

Table 1. Drivers per household combination from the Building Future study (TNO-ECN, 2007)

Household type	Convenience	Conscious	Costs	Climate
Single	●0000	•••00	••••	•0000
Two adults below the age of 60	$\bullet \bullet \bullet \circ \circ$	•••00	●●○○○	••000
Single parent family	•0000	$\bullet \bullet \bullet \bullet \circ \circ$	$\bullet \bullet \bullet \bullet \circ$	•0000
Family (two parents)	•0000	$\bullet \bullet \bullet \circ \circ$	$\bullet \bullet \bullet \bullet \circ \circ$	••000
Seniors above the age of 60	$\bullet \bullet \bullet \circ \circ \circ$	•0000	$\bullet \bullet \bullet \bullet \circ \circ$	••000

Characteristics per profile were formulated, based on interviews with singles, in case a 'single-household' would cope with that specific profile (TNO-ECN, 2007). Table 2 shows these characteristics per profile.

Table 2. Properties per profile with regard to energy demand of: heating, cooling, hot water, ventilation, lighting, cooking (not in original investigation, later added), and other electronic devices

Profile 1: Convenience	Profile 2: Conscious	Profile 3: Costs	Profile 4: Climate
Heating	Heating	Heating	Heating
• Heating on for comfort reasons	Heating not unnecessary on, on for comfort reasons	Heating not unnecessary onConscious with temperature	• Efficient heating installation available
 Quickly increase heating 		at home	• Heating on if other
 During day heating on, also while absent 	• First extra clothing, then heating increase	• During the night/in the morning, heating hardly on	options (e.g., extra clothes) are implied
• During night heating slightly lower		• Extra blanket or clothes	Good insulation
Cooling	Cooling	Cooling	Cooling
• Indirect by indoor sun shading (sun in bedroom)	• Use of available possibilities (indirect)	Conscious use of cooling possibilities	• Doors and windows open for cooling
• Air conditioning	• No cooling (electronic) devices		
Hot water	Hot water	Hot water	Hot water
• Hot water based on comfort	• Hot water as requested	• Hot water as requested	• Hot water only when necessary, heated by
Tab running until water			sunlight

has requested temperature			Water recycling	
Ventilation	Ventilation	Ventilation	Ventilation	
Constant ventilation by open windows	• Windows/air inlet mainly open	• Windows open if necessary, closed on time	• Windows and doors opened and closed for	
• During cooking, cooker fan on	Mechanical ventilation if necessary	 Mechanical ventilation if necessary, not unnecessary 	ventilationNo devices	
• Ventilation for fresh air		use		
Lighting	Lighting	Lighting	Lighting	
• Lighting on everywhere,	 Not unnecessarily on 	Lighting never	• Use of energy saving	
for convenience reasons	 Occasionally energy saving bulbs 	unnecessarily on Strategic use of energy 	devices like time clocks, solar lamps, etc.	
	• Use of decorative lighting	saving bulbs		
Cooking	Cooking	Cooking	Cooking	
• Fast food preparation; use of microwave	• Good planning of food preparation order;	• Cooking for more meals at once	 Fresh (season-related) products, not frozen 	
•	defrosting in fridge		One-pan meals	
<u>Electronic</u> equipment	<u>Electronic</u> equipment	<u>Electronic</u> equipment	Electronic equipment	
• All devices/ appliances	• Frequently on stand-by	 Not unnecessarily on 	Conscious when buying	
on stand-by or switched on	 Practical use, no constant on/off 	 Conscious when buying new appliances 	new appliances, also related to eco-taxes	
• Use by convenience, switching switching off while sleeping (night)			• Only really necessary equipment	

The user profiles indicate that not only building-related characteristics like heating, cooling, lighting, and ventilation are different within the different profiles, but also that differences are related to available electronic equipment and their use, and general household behaviour. Based on available energy use data (Milieucentraal, 2004; SenterNovem, 2007) the energy use per household profile is estimated (see Table 3).

Table 3. Energy use per household in GJ/year

	Energy use (GJ/yr)	Energy use (GJ/yr) per profile			
	Average	Convenience	Conscious	Costs	Climate
Heating	45,4	91,4	38,4	26,8	35,9
Cooling	2,1	2,8	2,1	0,8	2,0
Hot water	15,1	30,4	13,4	9,9	9,9
Ventilation	0,0	0,0	0,0	0,0	0,0
Lighting	1,9	2,8	1,4	0,9	0,9
Cooking	3,0	8,0	2,7	2,0	2,1
Washing/drying	2,7	3,0	0,8	0,8	0,8
Misc. electric	3,0	7,9	3,1	1,8	2,2
Total	73,1	146,3	61,8	43,1	53,8
% of average	100%	200%	85%	59%	74%

4. Statistical pattern generator

There are a significant number of models that generate demand profiles on the individual level at hourly basis (Paatero, 2006 and Widen, 2009), but there are only few validated models with which high

resolutions (i.e. <= 5 minutes) can be obtained (Knight, 2007). These models are based on existing statistical data and thus, can only deal with existing configuration of appliances in households. To study new configurations, specifically in energy efficient buildings, the model must be able to deal with new technologies for which no large scale data measurements are yet available. Examples of such technologies are heat pumps, balanced ventilation with heat recovery and local electricity generation like photovoltaics. Some of these technologies are time-dependent as they are continuous physical processes, i.e. the next state of the process depends on the history of the process. An example is space heating, which is characterized by the losses (related to the stochastic outside temperature) and thermal mass of the building. Thus, apart from a statistical pattern generator, there is also need for a dynamical pattern generator, which is described in the next section.

The statistical pattern generator models each appliance in the household individually. Which appliances are present in the household and what their yearly energy consumption is, depends on the chosen household profile. Four profiles have already been described in the previous section: Costs, Climate, Convenience and Conscious. A fifth profile available is the Dutch national average for a household.

Although each appliance is modeled individually, they can be grouped into categories, because their statistical characteristics are the same. Consider for example a refrigerator and a freezer. Although they have a different temperature working range, the principles of these two appliances are the same. The appliance turns on if the inner temperature is above the threshold and turns off when it reaches the lower threshold. Thus, both the freezer and refrigerator can be described as appliances that follow a periodic consumption pattern. Another example is a vacuum cleaner and a television. Both appliances are turned on at random times and the length of use can vary each time. The difference lies in the frequency of use, the probability the appliance is on at a certain time and the probability distribution of the length of use. But these are statistical characteristics. The six categories that are being distinguished are shown in Table 4, together with a short description of their characteristics. Most of these categories use "time of use" probability functions, which defines the probability that an appliance is turned on at a certain time. Because no data is yet available for the Netherlands to generate these functions, the function curves defined by Pratt et.al. (1989) are used. Furthermore, not only the power consumption of appliances is modeled, also their stand-by consumption, i.e. the power consumption when the appliance is not used, is also taken into account.

Category	Appliances	Characteristics
Lighting	Light bulbs	Depends on illumination and occupancy
Laundry	Washing machine, Drying machine	Fixed usage length
Dishes	Dishwasher	Fixed usage length
Cooling	Refrigerator, Freezer	Periodical pattern
Small appliances	Coffee machine, Television, Hair dryer	Variable usage length
Cooking	Range, Oven, Microwave	Variable usage length

Table 4: Categories used in the statistical pattern generator.

The energy consumption for lighting is strongly related to the (day)light levels in the household and the presence of active occupants. Extensive research has been performed in the past on how to model lighting demand. This has resulted in simplistic models that generate aggregated patterns (Stokes, 2004), but also more sophisticated models that model each light bulb present in a household individually (Richardson, 2009). The current method implemented in the pattern generator is based on the sun rise and sun set times and the times that household occupants sleep. The power used for lighting is calculated from the total number of hours the lights are turned on and the yearly energy consumption for lighting. A more sophisticated model will be developed in future research, which will be based on active occupancy and luminance.

Appliances used for the laundry and dishes (washing machine and dryer, dish washer) have the characteristic that their usage time is fixed as these appliances work with pre-defined programs. The energy profiles for these programs have been measured for a variety of devices, like the white laundry program for a washing machine plotted in Figure 2. The mean daily frequency of use can be calculated

using the total yearly energy consumption of the device and the consumption of one program. In combination with the time of use probability function, the pattern for these devices can be generated.

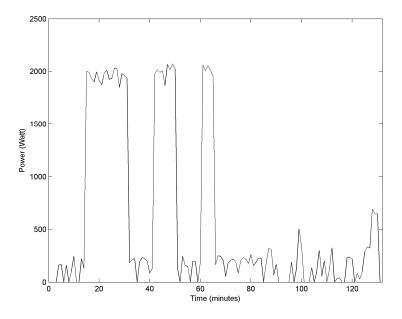


Figure 2: Measured electricity consumption profile of a washing machine for a specific program (white laundry, 60 degrees Celcius).

Refrigerators and freezers have the characteristic that their profile is approximately periodic, assuming that the ambient temperature for these appliances is approximately constant. The opening and closing of the refrigerator at selected time is not yet taken into account. The profiles of several of these appliances have been measured for multiple periods. The pattern is generated by repeating the measured one-period demand data, while scaling it to match the yearly energy consumption defined by the household profiles. To avoid that households with exactly the same profiles will also have in-phase refrigerator profiles, a random shift in the pattern is induced.

For appliances used to cook, like a microwave, a random usage time, based on an average usage time and a maximum deviation from the mean is selected for every time an appliance is used. These values have been estimated because of the lack of statistical data on this matter. The frequency of use is based on the yearly energy consumption and the average usage time. Again a time of use probability function is used to create the pattern for the appliance, together with either measured or a constant power profile to mimic the appliance demand behaviour.

Usage of general appliances strongly depends on active occupancy and resident behaviour. A sophisticated model has yet to be developed, but current profiles are randomly generated based only on a time-of use curve, where a mean daily frequency of 1 or 2 day⁻¹ is assumed, while the yearly energy consumption specified in the selected household profile is being maintained.

5. Dynamical pattern generator

The dynamical pattern generator is an improved version of the Building and Energy Equipment (BEE) model developed by ECN in collaboration with KEMA in 2003 (Visscher, 2004). A box model is used to simulate the building, in which the energy flows of transmission through walls, roof, floor and windows, irradiation through windows, ventilation and infiltration and the internal heat gain are used to calculate the internal temperature of the building. The model is fed with Standard Dutch year climate data from the

KNMI. Parameters for five typical Dutch types of residences (apartment, terrace house, end house, semidetached house and detached house) have been composed based on research by Bakker, 2000, Novem, 2001). The thermal behaviour of the building models for these five households has been validated against yearly heat consumption data and detailed TRNSYS models. Temperature set points for space-heating are based on the household profiles. The energy equipment models haven been divided into four sections. For a simulation configuration an appliance is chosen for each of these four sections. The devices are listed in Table 5. Each energy equipment section is implemented separately, without direct interaction with the other three sections. As a result, it is perfectly possible to take a shower, while heating up the building at the same time. However, in some households where domestic hot water and space heating is provided by one and the same device, this is not always possible in practice.

Domestic hot water	Space heating	Space cooling	Electricity generation
Electric boiler	Gas fired heater	Air conditioner	Photovoltaics
Close-in electric boiler Solar boiler	Heat pump Micro-CHP	Ground heater exchanger	Wind turbine
Heat pump boiler	District heating		
Micro-CHP boiler			
Gas fired boiler			
Gas fired heater			
District heating			

Table 5: Available energy equipment in the EPG's dynamic pattern generator.

All energy equipment is modeled by basic principles of that device, without dealing with details like startup times and flow temperatures, but the energy consumption of auxiliary devices in the system like pumps and fans are included. Equipment parameters like nominal power and efficiency have default values, but are configurable. Input for the energy equipment models comes from the building model supplemented with external data, like tap water demand and wind velocity. The output of these models comprises the consumption and production of heat, gas and electricity. The heat production or consumption (i.e. cooling) is fed back to the building model. This creates an indirect link between the equipment sections, as they use the building state, while also acting on it. Countermeasures have been taken to prevent that the space cooling and space heating would act at the same time, which would result in unrealistic energy profiles.

Part of the heat gain in the household comes from the statistical energy patterns, as appliances produces heat during operation. But not all of the heat from these appliances is added to the building energy balance. For example, water that is heated for cooking purposes is usually thrown away while still hot. Thus not all of the energy required to heat up the water is added to the building energy balance. For each of the six categories described in Table 4, a rough estimate of the percentage of energy added to into the building has been made, which is used to calculate the internal heat gain resulting from the statistical energy pattern.

6. Household occupancy

Occupancy data is needed for both the statistical (e.g. lighting usage) and dynamic pattern generation (e.g. heat gain). Two types of occupancies are being distinguished: active occupancy and sleeping occupancy. An active occupant is defined as a person who is in the house (or garden), but not resting or asleep. To model the occupancy in a household, a first order Markov-Chain technique is used such as described in (Richardson, 2008) together with the time use survey (TUS) data available for the Netherlands (SCP, 2007). The TUS data is available for 15 minute periods and thus, the occupancy time series data comprises 96 states per day. Each state indicates whether a person is away, sleeping in the house or active in the house. The concept of the first order Markov-Chain technique is that the next state only depends on the previous state, together with the probability of the state changing. These probabilities are held in transition probability matrices, which are deduced from the TUS data. A distinction is being made between all the 7 days in the week. No data for the Netherland was available for the occupancy correlation between multiple

persons in a household. Thus, the occupancy generator builds an occupancy time series for each individual person, without a link with the other persons in the household. Figure 3 shows a generated occupancy time series of a single person for a week, where the first day in the graph is a Sunday.

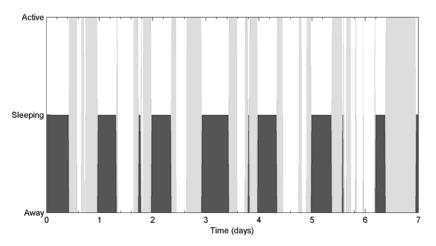


Figure 3: Active and sleeping occupancy for a single person.

7. Preliminary results

Figure 4 shows the electricity and gas demand pattern for an average Dutch household for the first week in March. The household is equipped with a high-efficiency gas-fired heater, which is used for both spaceheating and domestic hot water. The house is not actively cooled, nor does it have appliances that generate electricity. The first day in the figure (day 59 of the year) is a Wednesday. Gas consumption is expressed in power (Watt) instead of flow (m^3 /s), because the energy content of gas may differ per location and in time.

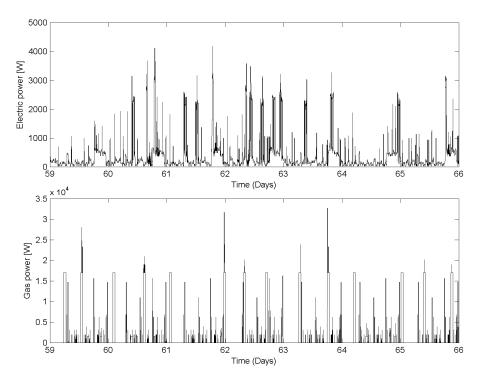


Figure 4: Generated demand patterns for gas and electricity in an average Dutch household for the first week of March.

8. Conclusion

Energy use in a home is determined by technical and architectural characteristics (building characteristics) on one hand and behaviour of the residents (household characteristics) on the other hand. The behaviour of the residents becomes relatively more important (i.e. of more influence) when developing ambitious, highly energy efficient building concepts. This implies the increasing need for robust 'user proof' building concepts.

To get a grip on the effect of user behavior on energy performance, drivers for energy saving behaviour have been studied. Five typical household profiles have been composed. Each profile has a unique composition of household appliances, including their total yearly energy consumption. Furthermore, models for five (residential) building types have been defined and the energy patterns of several individual appliances have been measured. Based on a Dutch "time of use" survey, an occupancy generator has been developed to model the presence of residents in the household. Altogether, yearly electricity and heat demand profiles for all combinations of household profiles and building types can be produced.

The EPG enables not only the study of energy consumption due to occupant behaviour, but also the variability at short time-scales. The final EPG will be a validated software tool which takes the sensitivity of specific user behaviour on energy consumption into account. Therefore, unique user profiles can be developed by selecting specific user characteristics. Also, the number and type of household appliances are adjustable. On the other hand, the EPG will be able to produce cumulated patterns of more than one household on a higher level i.e. district level. This makes the EPG a versatile tool, visualizing the impact of occupant behaviour on energy consumption.

9. Outlook

In order to realize the EPG as described above, research on user behaviour effects will be continued and intensified. A questionnaire will be sent to 10.000 occupants, in order to acquire more data on configuration and use of household appliances. This data is used to generate the time-of-use probability functions. Also, drivers for energy saving behaviour will be surveyed and the link with socio-demographic parameters will be established. This way, the five user profiles can be further improved.

Additionally, measurements of electricity and gas consumption (and production) are conducted in a large number of households. These measurements will be used to validate the EPG. Measurements will involve entire households, but also individual household appliances and categories of appliances as defined in Table 4. Furthermore, new energy-efficient appliances like mobile air-conditioning and tri-generation units will be introduced to study their effect on the household energy consumption pattern.

Future research activities also involve the improvement and fine-tuning of some of the statistical models. Furthermore, the ambition is to use measured profiles for domestic water consumption, in stead of using fixed profiles according to Dutch building regulations.

Besides the original objective to design robust, high efficiency buildings, the EPG has other useful applications. Application of the EPG can also be foreseen in the area of power and heat management, where supply and demand of energy can be balanced on different aggregation levels, i.e. household or district level. The EPG can predict how much energy is desired at any time of the day, showing clearly the variability in power. This energy demand can be supplied by i.e. local (renewable) energy generation elsewhere. This way, the EPG can also be of importance in the design of (intelligent) electricity grids as it provides dynamics in the grid's loads. Also, the contribution of renewable energy sources can be optimized, which can reduce the use of fossil fuels.

Another application is analysis of the effect of user behaviour on indoor comfort. The use of household appliances increases internal heat production affecting thermal comfort. This heat production may result in not meeting comfort standards. The EPG can show to what extent user behaviour affects indoor comfort.

References

- Bakker, E.J., Zondag, H.A., Strootman, K.J., Visscher, K., (2000), Warmtevraagpatronen voor ruimteverwarming van bestaande woningtypen in Nederland, ECN internal report, ECN-Memo-00-033.
- Groot, E. de, Spiekman, M., Opstelten, I.J., (2008), Dutch Research into User Behaviour in Relation to Energy Use of Residences, Proceedings PLEA 2008 - 25th Conference on Passive and Low Energy Architecture, Dublin, Ireland, 22-24 October 2008, 5pages
- Knight, I., Ribberink, H., (2007), European and Canadian non-HVAC electric and DHW load profiles for use in simulating the performance of residential cogeneration systems, Chapter 8: Electricity demand profiles for Canada, IEA Annex 42 Subtask A final report.
- Milieucentraal, (2004), Website Data about average energy use. Available at http://www.milieucentraal.nl/
- Novem, (2001), Referentiewoningen bestaande bouw, ref nr. 1DUWO01.01.
- Paatero, J.V., Lund, P.D., (2006), A model for generating household electricity load profiles, International Journal of Energy Research, Vol 30, Issue 5, p273-290.
- Poortinga, W., Steg, L., Vlek, C., Wiersma, G., (2003), Household preferences for energy-saving measures: A conjoint analysis, Journal of Economic Psychology, Volume 24, Issue 1, February 2003, Pages 49-64
- Pratt, R., Conner, C., Richman, E., Ritland, K., Snadusky, W., Taylor, M., (1989), Description of electric energy use in single-family residence in the Pacific NorthWest, DOE/BP-13795-21, Pacific NorthWest National Laboratory.
- Raaij, W.F. van, Verhallen, T.M.M., (1983a), A behavioral model of residential energy use, Journal of Economic Psychology 3 (1), pp. 39–63.
- Raaij, W.F. van, Verhallen, T.M.M., (1983b), Patterns of residential energy behaviour, Journal of Economic Psychology 4, pp. 85-106
- Richardson, I., Thomson, M., Infield, D., (2008), A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings, Vol 40, Issue 8, p1560-1566.
- Richardson, I., Thomson, M., Infield, D., Delahunty, A., (2009), Domestic lighting: a high resolution energy demand model, Energy and Buildings, 2009, Vol 41, Issue 7, p781-789.
- SenterNovem, (2007), Cijfers en tabellen 2007, SenterNovem brochure, 88 pages. Available at http://www.senternovem.nl/mmfiles/Cijfers en tabellen 2007 tcm24-222867 tcm24-247452.pdf
- SCP, (2007), Tijdsbestedingsonderzoek 2005
- Stokes, M., Rylatt, M., Lomas, K., (2004), A simple model of domestic lighting demand, Energy and Buildings, Vol 36, Issue 2, p103-116.
- TNO-ECN, (2007), Samenvatting van de resultaten van onderzoek door studenten van de InHolland Hogeschool naar energie en huishoudprofielen in 2005, memo Building Future TNO-ECN (unpublished data). [in Dutch]
- Visscher, K., (2005), WEI: een universeel Woning- en Energie Installatiemodel als bouwsteen voor het voorspellen van de energievraag van woonwijken, ECN report, ECN-I--05-002, [In Dutch].
- Vringer, C.R., (2005), Analysis of the energy requirement for household consumption, Ph.D.-thesis University of Utrecht, Milieu en Natuur Planbureau, Bilthoven
- Widen, J., Lundh, M., Vassileva, I., Dahlquist, E., Ellegard, K., Wackelgard, E., (2009), Constructing load profiles for household electricity and hot water from time-use data, Energy and Buildings, Vol 47, Issue 7, p753-768.