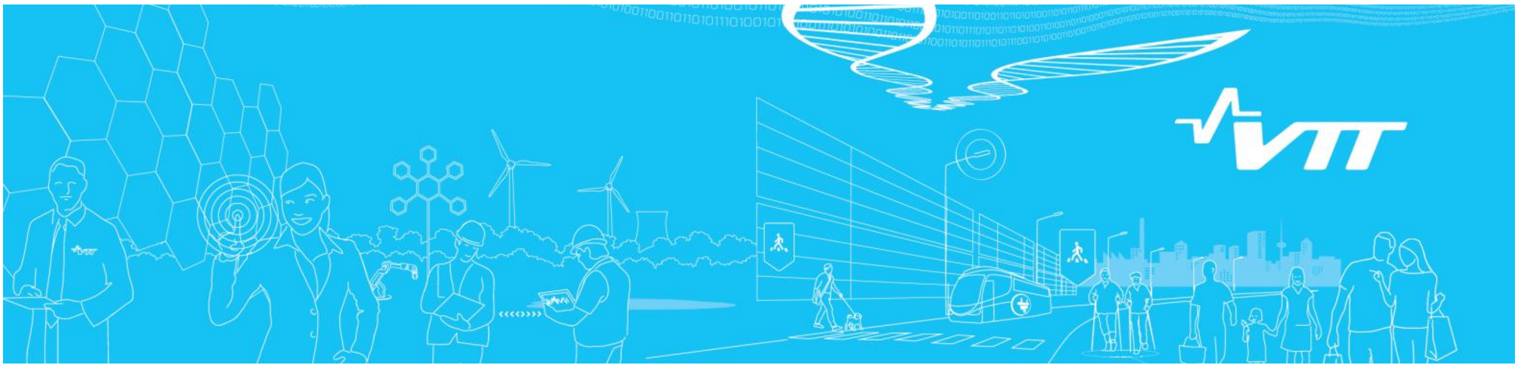

RESEARCH REPORT

VTT-R-01370-15

SGEM 3FP D4.2.7/ 4&5 FP D4.3.12

Load profiling using building blocks

Authors: Göran Koreneff

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Summary

There are 46 load profiles in use in Finland and they stem from sparse and infrequent measurements in the 1980's and early 90's. With new hourly meters in use, measurements exist to update them. However, the main obstacles to continue using the existing classification of 46 load profiles are the overwhelming changes that take place at the end-users, e.g. different kinds of heat pumps, for use as main or auxiliary heat source, PV, solar thermal panels and electric vehicles. These part-loads do not only change the annual energy consumption of households, they also change the profile and in very decisive ways.
The main objective behind this report is to study the feasibility and construction logics of a load profile system based on sub-client load blocks, part-loads, which could be an extension to the load profile models in use nowadays in Finland. The main innovation is the realisation that the loads of the future will more and more consist of distinct and differently behaving part loads, which are non-correlating causes and which require very different control algorithms. One difficulty with our approach will lie in constructing algorithms for part-load identification at end-users and assessing their part load annual energies and control behaviour. Another will lie in formulating generic part-load profiles and their behavioural algorithms. And a third difficulty will lie in confidence formulations and calculations.
The basic building blocks approach is similar to the traditional with the exception that one user can have several sub-profiles, and some of them can be negative. With a few new sub-profiles, for example the electricity saving profile of an air-air heat pump in an electric heated house, a PV profile, a couple of electricity saving solar thermal profiles and a couple of electric vehicle charging profiles, we have a starter pack. For a more advanced building block approach, some part-loads profiles need to be algorithm based, locally oriented and weather sensitive.

Confidentiality	Public

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Written by	Reviewed by	Accepted by
Göran Koreneff Senior scientist	Seppo Hänninen, Project manager	Tuula Mäkinen, Head of Research area

VTT's contact address

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Preface

This work was carried out in the Smart Grids and Energy Markets (SGEM) research program coordinated by CLEEN Ltd. with funding from the Finnish Funding Agency for Technology and Innovation, Tekes. I also wish to thank all the SGEM partners, among others my working task, WT 4.3, colleagues Pekka Koponen at VTT, Antti Mutanen at TUT and Harri Niska at UEF, my work package manager Pertti Järventausta, and SGEM manager Jani Valtari, who supported the international load modelling workshop organised by our task. I also like to thank Atte Löf and Riku Pasonen for the expedite delivery of solar data.

This report is the deliverable 4.2.7 of Working Task 4.2 in the 3rd funding period of SGEM, but is also partly a stand-in for the cancelled deliverable 4.3.12 of the 4th&5th funding period and relates thus to the deliverable 4.3.11, the building block test prototype.

Espoo 28.2.2015

Contents

Abbreviations

A	Ampere
AAHP	Air-air heat pump
ABBA	Advanced building block approach
AMR	Automatic meter reading
AWHP	Air-water heat pump
BBBA	Basic building block approach
CHP	Combined heat and power
COP	Coefficient of performance
DG	Distributed generation
DH	District heating
DHW	Domestic hot water
DR	Demand response
EAHP	Exhaust air heat pump
EV	Electric vehicle
FEV	Full electric vehicle-
FiT	Feed-in tariff
FP	Funding period in SGEM
GSHP	Ground source heat pump
ICE	Internal combustion engine
kW	kilowatt, equal to 1000 W
Micro-CHP	CHP at house level
MW	Megawatt, equal to 1000 kW
MWh	Megawatt hours, equal to one hour of 1 MW
PHEV	Plug-in hybrid electric vehicle
PV	Photovoltaic
RES	Renewable energy sources
RES-E	Electricity from renewable energy sources
SGEM	Smart Grid and Energy Management –research programme
SPF	Seasonal performance factor
ToU	Time-of-use
UK	United Kingdom
V2G	Vehicle-to-grid
W	Watt

1. Introduction

There are 46 load profiles in use in Finland (SLY 1992, Seppälä 1996) and they stem from sparse and infrequent measurements in the 1980's and early 90's. The number of customer end recordings behind each profile varies. For single family house profiles, the number of recordings behind them is between 4 and 56, but it is good to remember that each recording might be just a few months long. They are also from different seasons and years. The profiles have nevertheless proven their usefulness for the network utilities. VTT updated these models partially in 2002, but access to the updated models is restricted to the then project partners.

With automatic meter reading (AMR) being on the march into every household, the availability of measurements will be on a very different scale. Thus, updating the national profiles or even creating new local network dependent profiles will be possible, even updating or automating the profile classifications (see e.g. Mutanen 2010, Mutanen et al. 2011a, b). However, especially for network long-term planning purposes, national easy-to-use and clearly defined profiles will be advantageous.

The main obstacles to continue using the existing classification of 46 load profiles are the overwhelming changes that take place at the end-users' consumptions. A lot of new significant part-loads have been or are to be introduced in households. The new additional part-loads in the households do not only change the annual energy consumption, they also change the profile and in very decisive ways. In addition, parts of the loads are temperature dependent, other parts not. Scalability of load curves is another problem, as even if the right class is used, the internal share of the part-loads might be wrong for a single customer. The question is, shall we nevertheless try to introduce new profile classes for all the main combinations, use the old classification, or is there another solution?

The building block research here is based on the research recommendations (Koreneff 2010) from the Inca-project.

1.1 Goal

The main objective of the subtask 4.2.2 of 3rd funding period (FP) of the Smart Grid and Energy Management (SGEM) project is study the feasibility and construction logics of load profile system based on sub-client load blocks, which could be an extension to the load profile models in use nowadays in Finland. As the resources in SGEM of 4&5 FP where cut down and D4.3.12 of 4&5 FP was cancelled, the publishing of this report was delayed to include also newer developments.

1.2 Description

The division of customer loads into smaller building blocks is not a new concept. This has been done several times before, see e.g. Paatero (2006), but earlier studies have focused on household appliances such as white goods, coffee machines, lighting, stows, televisions, computers etc. This type of approach has it merits, for example when studying how changes in the impact factor of different appliances will affect the loads of the future. The annual demand for specific uses is also being investigated with some years' intervals, the most recent study in Finland being (Adato Energia 2013).

Our focus is different. Our target is to achieve as good as possible hourly load profiles for the utilities to use both in the short term and in the long term. Especially household loads are becoming more and more intricate and differing. The main innovation is the realisation that the loads of the future will more and more consist of distinct and differently behaving part loads, which are based on more or less uncorrelating causes and which require very different control algorithms:

- electric heating is based on the heat demand, which in turn is based on the temperature difference between the house and the outside, and may be affected by additional major factors
- the behaviour of electric vehicles depends on previous road usage, and may depend on intelligent charging algorithms
- distributed generation (e.g. PV, micro-CHP, wind power) of electricity has the opposite direction, as it diminishes other loads in a household and may even result in the household being a net power producer in the grid.

The benefits of a part-load based approach to the end-user's electricity demand are thus the ability to use more specific control algorithms while still retaining the simple base structure of load profiles their use.

The disadvantages are the need for part-load separation algorithms (at least on an annual energy basis) and a more complex control structure. However, as load models in use today have an outside temperature dependency function already, the use of control structures does not necessitate a reconstruct of the working methods, but an extension.

One difficulty will lie in constructing algorithms for part-load identification at end-users and assessing their part load annual energies and control behaviour. Another will lie in formulating generic part-load profiles and their behavioural algorithms. And a third difficulty will lie in confidence formulations and calculations.

1.3 Limitations

This study is about the feasibility of a building block based load profile system, what must be taken into account and what questions are deemed to be the most difficult to answer. To assess the feasibility, the logical structure of thus a system has to be designed and relevant load building blocks assessed. However, no prototype is meant to be built nor any actual load profiles constructed nor is the issue of confidence intervals approached.

As an extension to the original goal, in 4&5 FP a prototype system for the management logics of part-load blocks for an end-user is tested. The testing will also reveal what issues and problems related to confidence intervals arise.

1.4 Methods

Existing Finnish load curves from the 1990's are used as basic reference. Some derived load curves related to electric heating, heat pumps, electric vehicles (EV) and distributed generation (DG) will also be used for the assessment of the concept.

2. The logic behind building blocks

2.1 Justification for building blocks

The idea of using building blocks for household sub-loads with very different characteristics was first brought forth by Koreneff (2010). Households consist of many distinct type of sub-loads, each having their own characteristics and dependencies demanding tailor made algorithms:

- Household appliances are all very dependent on the human behaviour in the house, and often complimentary and correlating. Most appliances are used when there is somebody at home, thus correlating with each other and with the human schedule. On the other hand, a person watching television may use the computer less, have less lighting on and leave the stove alone.

- Electric saunas can be part of household appliances or separate items. They are only dependent on human behaviour. Saunas in turn affect the needs for electric space and hot water heating.

- Electric heating of space is to a large degree unrelated to human presence, and correlating highly to the weather; the load curve itself depends also on the type of heat storage available and on the tariff system. Electric heating can also be influenced by several major factors such as heat pumps, solar heat, wood stoves etc.

- Electric heating of hot water (domestic hot water, DHW) is dependent on both human behaviour and domestic hot water storage size and type.

- Electric vehicles' loads depend on their location, their electricity storage situation, and, in the future, probably on different load strategy options.

- Photovoltaics are negative loads, that is, they decrease the household load and will in all probability even turn the household to a net produce during some hours. Photovoltaic production is dependent on the local direct and indirect solar radiation (including shading objects) and the installation angle.

- Micro-CHP diminishes household electricity loads and demand for electric heating. It is dependent on these demands, heat storages and operating guidelines.

- Heat pumps use electricity to form heat with an extremely good efficiency. Air-to-air heat pumps can produce e.g. 2-5 times (the coefficient of performance, COP) as much heat as electricity is used. The COP varies with outside temperatures, at extreme cold spells it can even be below one.

- Solar thermal production is a negative heat load, that is, it decreases the household demand for electric heating. The production is dependent on the local direct and indirect solar radiation and heat storages.

- Wood stove is a negative heat load, that is, it decreases the household demand for electric (space) heating. The production is dependent on human behaviour and the heat storage capability of the stove or connections to other heat storages.

Many part-loads are also uncorrelated. If a house has a heat demand of 40 MWh per year, it doesn't mean that the household electricity is twice as high compared to a house with a heat demand 20 MWh per year. Traditional profiles, however, assume that it is so. They therefore have the best match when used for loads of a similar size as the ones which were used as basis for creating them.

2.2 The number of household profiles

There are currently 12 load profiles for single family houses:

- 110 direct electric heat, water boiler <300 liter
- 120 direct electric heat, water boiler =300 liter
- 130 direct electric heat, floor heating >2kW
- 210 partial storage electric heat, short disconnect periods
- 220 partial storage electric heat, long disconnect periods (7-22)

- 300 full storage electric heat, (7-22)
- 400 heat pump
- 510 dual heat, flat tariff
- 520 dual heat, night tariff
- 530 dual heat, seasonal tariff
- 601 no electric heat, no electric sauna
- 602 no electric heat, electric sauna

In the future, we would need a tremendous amount of profiles, if we would like to identify clearly different households:

- Four types of basic one family houses heating modes (no electric heating, direct heating, partial storage heating, full storage heating)
- Four types of basic main electric heating sources with different behaviour (direct electric, ground source heat pump (GSHP), air-water heat pump (AWHP), and exhaust air heat pump (EAHP))
- Six additional heat source possibilities with different behaviours (no additional, air-air heat pump (AAHP), AWHP, solar heat, micro-CHP, and a manual source such as stove/fire place)
- Five different electric vehicle (EV) constellations (0…2 pieces, smart or dumb charging)
- Three types of additional micro generation possibilities (none, photovoltaics (PV), wind power)
- Electric sauna or not

This would result in (1+3*4)*6*5*3*2 = **2340** distinctive load profiles for one family houses, which is not manageable. Some combinations can be left out, others combined, but there will still be a lot of major classes left. Even with AMR, it would be very difficult to get enough measurements for all the classes, as some combinations are rarer than other.

2.3 Addition of positive and negative part-loads

The approach of having sub-user part-load profiles in load estimation is a simple extension of the nowadays system using static profiles. Instead of having one profile per user, we would allow for several profiles. This means of course that the user's annual energy also has to be split into several sub-parts. This basic building block approach (BBBA) also demands that we allow negative profiles and, as not all is or can be measured, that some profiles are based on models as well. The profiles would be as static as they are today, with at most one adjuster, for example outside temperature. In addition, if we look at demand response (DR), we can pinpoint in what part-load the response takes place and we can include the DR algorithm as an extension.

During the course of the project we have also come to the conclusion that, at least for part of the loads, a more advanced building block approach (ABBA) could be useful. ABBA includes new operators such as multiplication and max and allows for modelling the profiles on the fly, using local weather data, other profiles and control algorithms, especially for storages. The use of algorithms improves both the accuracy and sensitivity of load models in respect to outside occurrences. In addition, load estimation would not be only at the substation level, but also on the household level utilising all kinds of existing state estimations tools.

The main approach of this study is the BBBA, whereas ABBA is introduced as an object of further research.

The basic building block approach suggests that we construct a user's load using part-load profiles, which can be added or subtracted. For example, a customer's load may be:

+ household electricity
+ DHW
- solar heat panel for DHW (=savings)
+ direct electric heating
- AAHP in electric heated house (=savings)
+ AAHP during the summer for cooling
+ one PHEV without smart charging

Instead of adding a new operator, subtraction, we can instead use negative profiles. If we for example look at a house *i,* then the aggregated load P_i will be

$$P_i = \sum_x P_{x,i} \quad \forall \; x \in B_p \tag{1}$$

where
$P_{x,i}$ is the subload x in house i and
B_p is group of relevant part loads.

$P_{x,i}$ can then be either calculated using a dynamic model or using part load profiles. When using profiles, we get the sub-load of type *x* for house *i*:

$$P_{x,i} = \sum_{\mathrm{x}} W_{i,\mathrm{x}} \, P_{p,\mathrm{x}} \;\forall \; x \in B_p \tag{2}$$

where
$P_{p,x}$ is the load profile for sub-load x
$W_{i,x}$ is the annual energy of house i for the sub-load x.

As can be seen in the example, the most complex sub-part will be formed by heating, including space and DHW. Whereas EV's or PV's are independent instances, heat related items are all interconnected. This interdependency will be analysed more thoroughly in the next Chapter. Micro-CHP will be both heat and electricity related, but although micro-CHP's are slowly penetrating some of the European markets, e.g. Germany and UK, mostly due to exorbitant support, they are not expected to conquer the Finnish market in the nearest decades. Their profitability is none-existent today even looking at just variable (=fuel) costs.

3. Different building blocks of load profiles

3.1 Household appliances

All households have household appliances. The utility has no way of knowing the appliances in a specific household without extraordinary measures: interviews, none-intrusive automatic load monitors, etc. Although the use of household electricity can be higher in a large house than in a small house or in an apartment and it can differs quite strongly from one to another, on average we can accept the assumption that the use of household electricity is very similar in all households. We can only build a better system that is not based on this equivalency assumption if we have additional information of the households, for example the living area (m^2).

Local geographical settings may also influence the household profile, as lighting loads have become more and more important in the households. The nights are longer in the North during the winter and shorter during the summer. However, due to the forced switch to low wattage light bulbs, and with the growing penetration of energy saving lamps, electricity demand for lighting demand is also constantly changing.

As automatic meter reading is improving our knowledge of end-user loads, we can also easily construct updateable local household electricity profiles using only those household loads that do not have electric heating etc. in any form. Here clustering methodology can be used (Mutanen 2010, Mutanen et al. 2011a,b).

As already noted, all households have household appliances and therefore household electricity is easy to profile, including standard deviations. Geographic differences can be taken into account using longitude and latitude parameters or using local household electricity profiles, but on the other hand, the geographically based lighting differences are just a (assumingly small) part of the total load variations. Existing load profile for household electricity can well be used, for example type 601, “One family house, no electric heat, no sauna”, see example in Figure 1.

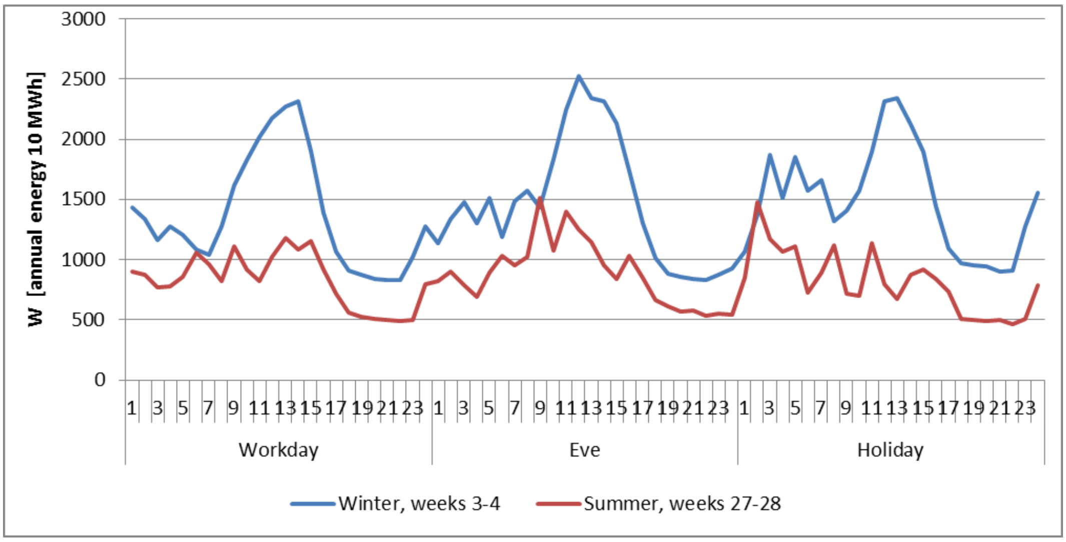

Figure 1. Load profile 601 in W for one family house, with no electric heat and no sauna, during selected winter and summer weeks and according to weekday type. Estimates are based on index series and here for a user with an annual energy of 10 MWh. NB. The days here are traditional power utility day 07:00-07:00.

3.2 Electric heating

The total heating demand could be assessed by separately measuring the electricity demand for heating in houses with no additional auxiliary heat sources.

To estimate the heating demand from the load profiles is a bit tricky. Simplified it could be done by subtracting the household electricity from the load profile of a direct heated house. In Figure 2 we present the results of subtracting the load profile of 601, a single family house without electric heating or sauna with an annual energy of 5 MWh, from the load profile of 110, a directly electric heated single family house with an annual energy of 25 MWh. As can be seen, the results can’t be used without modification, as the loads are occasionally negative. From the summer curves we can deduct that the measurements behind the profile

110, electric heated houses come from houses which follow a traditional day-night tariff rhythm, where at least the DHW is heated beginning late in the evening.

The electric heat demand can also be estimated using model results. To get a generic profile, we would need to model different types of households at different locations and weather years and then use a weighted representative average. It is easier to get local profiles, as the target is more restricted and measurements can be used.

In ABBA, the heat demand profile can also be based on the simulations with house heating models, especially if we want to use algorithms for storage behaviour or optimisation. The heat demand model could further be split into space heating, see e.g. Figure 3, and DHW demands, further increasing the possibilities to use e.g. storage control algorithms.

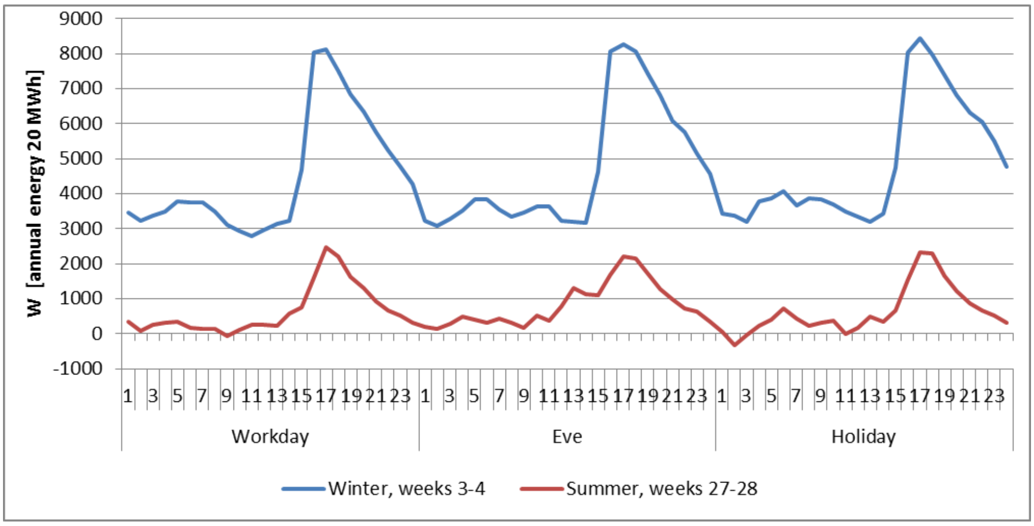

Figure 2. Resulting heating profile when load profile 601 of a one family house (5 MWh per year), with no electric heat and no sauna, is subtracted from load profile 110, a direct electric heated one family house (25 MWH per year), during selected winter and summer weeks and according to weekday type. Load profiles110 and 601 are here based on index series. NB. The days here are traditional power utility day 07:00-07:00.

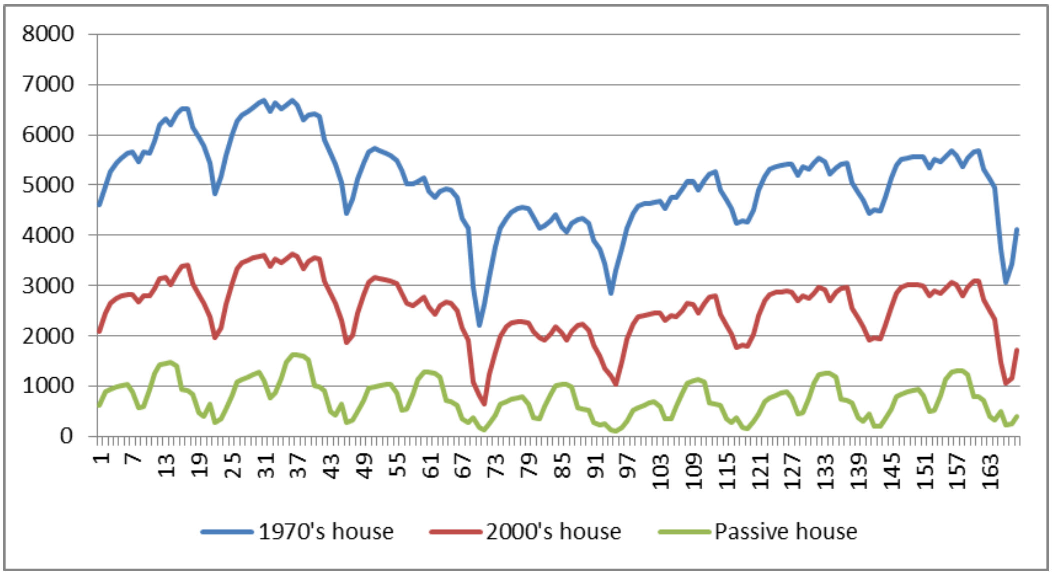

Figure 3. Modelled space heat demand for three different kinds of houses for a 7 days spell in winter using measured temperatures with a small warming spell in the middle of the timespan. Data source: SGEM WT3.6 (FP1), see Laitinen et al. 2011.

The daily evening dips in the heating demand are related to internal heat sources such as people and appliances.

Modelling of the electricity use for space and DHW heating can be a complex task. The BBBA way is to stay with electricity loads and profiles. That means that we use a basic electric heat profile together with negative auxiliary saving profiles such as solar heat or the saving part of an AAHP as presented in Equation (3). Storage behaviour is not specifically modelled in this approach but can be part of the basic electric heat profile, as it is with nowadays profiles in use.

$$P_{eh} = \max\ \left(0;\ \sum_{\mathrm{i}} \sum_{\mathrm{a}} W_{i,a}\, P_{p,a}\right)\ \forall\, i \in H,\ a \in B_{p,eh}$$

3

where
P_{eh} is the net electricity use for heating purposes,
H is the group of houses studied,
$B_{p,eh}$ is group of relevant building blocks, i.e. sub-profiles, for electric heat loads
$W_{i,a}$ is the annual energy of house I for the sub-profile a, and
$P_{p,a}$ is the profile for sub-load a.

Relevant sub-profiles are, for example, all the existing electric heat profiles as well as negative saving profiles such as solar heat and auxiliary AAHP saving profile. The AAHP saving profile is the same as the difference between the heat produced and electricity used of an AAHP.

First tests of course showed that using negative profiles, there is a risk of ending up with negative loads for some hours. This can be either allowed, resulting in an error, or restricted, for example by restricting the resulting load to non-negative values as the max operator in Equation (1) does. For a group of houses it is inexact, as it so to say allows for house wise negative numbers. If we allow for more time consuming house wise calculations as in ABBA, Equation (1) can be rewritten in the form where the max function is exact for a single house:

$$P_{eh} = \sum_{i}\left(\max\ \left(0;\ \sum_{\mathrm{a}} W_{i,a}\, P_{p,a}\right)\right)\ \forall\, i \in H, a \in B_{rel}$$

4

Another weakness of the formula is when using, for example, heat pumps with a COP ≠ 1 as the main electric heating source. Solar heat can be subtracted from direct electric heating without conversions, but not from GSHP electricity, where heat is produced with, e.g. a COP of 3. One easy way out of this dilemma is to model all heat pump houses in separate groups and respectively resize the auxiliary heat output. A more generic way would be to model also GSHP-houses as using direct electric heat profiles as basis, and then multiply the house wise sum results with coefficient c_i,:

$$P_{eh} = \sum_{i}\left(\max\ \left(0;\ c_i\ \sum_{\mathrm{a}} W_{i,a}\, P_{p,a}\right)\right)\ \forall\, i \in H, a \in B_{rel}$$

5

where
c_i is 1 for non-GSHP heated houses and $1/COP_i$ for GSHP heated houses.
COP_i is the COP profile for house i.

Here we have assumed the COP of a house to be a profile, i.e. time dependent. This is especially true where the GSHP peak capacity is dimensioned, e.g. to 60% of the peak demand and where the missing heat is produced with an electric boiler. This formula can also be extended to exhaust air heap pump heated houses or air-water heated houses, with their own type of COP profiles.

An alternative for Equation (5) would be to have the GSHP electric heat profile as basis and adjust the auxiliary heat sources with factor $c_{i,a}$,where it would be 1/COP_i for a ϵ solar heat, AAHP saving profile, stove etc. and 1 for the rest.

The equations work both for total electric heat as for space and DHW heat separately. The separation of space and hot domestic water heating is a demanding task and brings forth new uncertainties. It might necessary, if we want to simulate the working of different storages, that is, hot water boilers and partial or full space heat storages and auxiliary heat sources such as solar heat or AWHP.

To include storage dynamics we have in any case to also start use heat profiles and go at it house wise. The basis heat demand can be represented by the direct electric heat profile, and the auxiliary heat sources are managed quite similarly as in Equation (4):

$$Q_{eh,i} = \max\ \left(0;\ c_i \sum\nolimits_{\mathrm{b}} W_{i,b}\ Q_{p,\mathrm{b}}\right)\ \forall\ b \in B_{heat,rel} \qquad 6$$

where
$Q_{eh,i}$ is the resulting net heat demand to be satisfied with the main electric heat source,
$B_{heat,rel}$ is group of relevant heat building blocks, i.e. sub-profiles,
$W_{i,b}$ is the annual energy of house i for the sub-profile b, and
$Q_{p,b}$ is the normalised heat time series of sub-profile b.

The management of auxiliary heat pumps differs from the electric based calculations. For example, the total AAHP heat production is used as a demand decrease, not only the free energy part. In addition, as electricity is used, it, $_{Peh,AAHP,i}$ has to be added as a separate item, (1/$COP_{i,\ AAHP}$) $W_{i,AAHPneat}$ $Q_{p,AAHOheat}$, to the net electric heat load P_i. The net electric heat load, $P_{eh,i}$. is inother words equal to the sum of $_{Peh,AAHP,i\ a}$ and the electricity, $P_{eh,f,i}$, needed for the net free heat demand.

For direct electric heating, we get $P_{eh,f,i} = Q_{eh,i}$, assuming electric heating has an efficiency of 100%, which is a safe assumption with the error levels of load profiles, and no storage is used. If storages are explicitly used, we have to add an algorithm, but if their use is an implicit part of the total basis heat demand profile, there is no need for that.

As AAHP and GSHP can also be used for cooling during the summer heat spells, it should also be noted and separately included in the house balances, but not in the heat or electric heat balances.

3.2.1 Main electric heat sources

The heating demand is satisfied by heat sources. If the only heat source is electricity, then all of the demand is satisfied through electricity. With direct electric heating, the heat demand and the electricity supply for heating match each other. Heat pumps have a better performance, so perhaps only a third of electricity is needed to supply the heat demand. We can model different ground source, air-water and exhaust air heat pump installations, but there are a lot of uncertainties. Is the GSHP capacity 100% of the peak demand or only 60%, how large a share can the EAHP manage, what are the COP's and how does the weather affect the performances?

3.2.2 Auxiliary electric heat sources

Air-air heat pumps or air-water heat pumps are commonly used as auxiliary heat sources both in direct electric heated houses as in houses heated by other means. In electric heated houses, the use of heat pumps has an energy saving effect. This can be modelled either as a resulting profile, where the problem lies in that individual constellations can be very different (low heating demand but much AAHP capacity compared to high heat demand and low AAHP capacity), or using two separate profiles, one for direct electric heating and one for electricity saving from AAHP or AWHP. The Figure 4 shows the electricity saving (= is negative) curve of an AAHP.

The outside temperature affects the performance of the air heat pumps. The temperature goes from -4°C to -8°C in the first days, where after it rises to around zero before starting to cool down to -4°C again-. The heat production is also dependent on the in-house air temperature, which in turn depends on the human behaviour both through body heat as appliance usage. This is here assumed to be pronounced during weekend evenings and especially Sundays, the two saving dips in the middle.

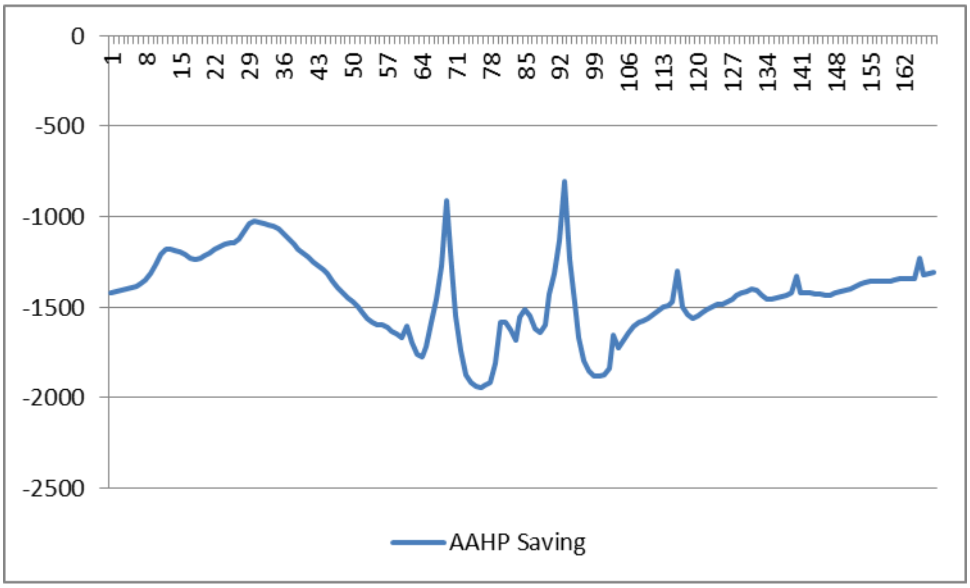

Figure 4. AAHP saving curve for the same seven days as shown in Figure 3. The warmer weather in the middle of the time span improves on the COP and thus increases the savings. Data source: SGEM WT3.6 (FP1), see Laitinen et al. 2011.

In pellet, oil or district heating heated houses the constellation is simpler. Here auxiliary electric heat sources, see Figure 5, just add to the demand of electricity.

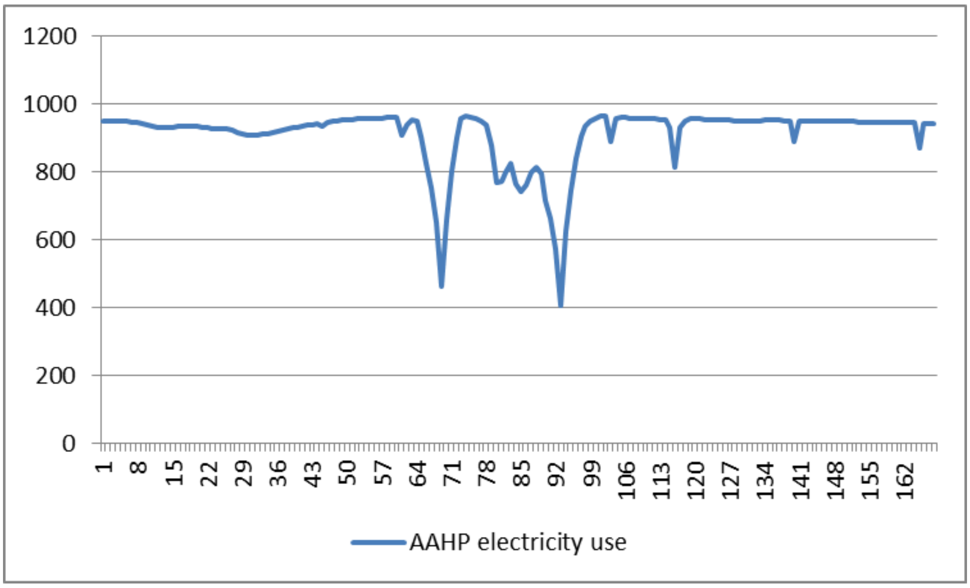

Figure 5. AAHP electricity use as an auxiliary heat source in a non-electrically heated house for the same seven days as shown in Figure 3. Data source: SGEM WT3.6 (FP1), see Laitinen et al. 2011.

3.2.3 Auxiliary other heat sources

Solar heat production can be modelled in much the same way as PV production, although PV can further be restricted by the electronics. Solar radiation has strong seasonal variation, see Figure 6, although the tilt of the panel can smooth the production curve. The main use of solar heat is for DHW. Whereas excess PV production can be delivered to the network, this is not so for solar heat. Heat production seldom coincides with heat consumption, so a local heat storage is of essence.

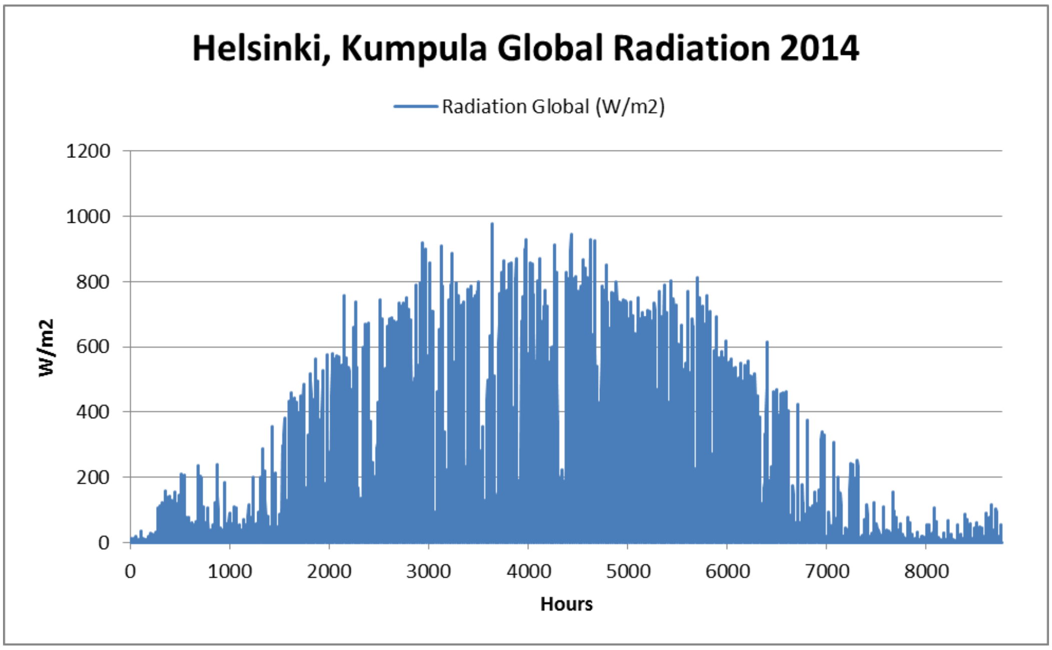

Figure 6. Solar radiation as W/m^2 at Kumpula in Helsinki in 2014.

Therefore the solar heat production profile cannot be directly subtracted from the heat demand on an hourly basis, but should be profiled to match electric heat daily variation of the main profile while matching the produced daily energy. On a seasonal basis, solar heat can cooperate with ground source heat pump systems, where excess heat in the summertime is stored in the ground and thus improves the efficiencies during the heating season.

Wood or pellet stoves can be assumed to be already implicitly included in the main electric heat profiles, as they are based on real measurements. In an ABBA systems, if so desired, auxiliary wood and pellet stove behaviour can be modelled using statistics and heuristic. The local point of view can enhance the heuristics. In a rural environment, the use of stoves is assumed to be more pronounced than in an urban environment, for example.

3.2.4 Storage behaviour

As already noted, storage behaviour is implicit in the BBBA main electric heat profiles With the increase in DR use of storages as well as a more widespread use of direct spot price based tariffs, more and more focus needs to be put on the storage behaviour. Existing profiles assume that electric heated houses have night-day tariffs and are mainly heated during the night. The heating algorithms are also assumed to be simple: fill up the heat storage immediately the low price tariff slot starts. Utilities and end-users have now also started other behaviours, for example load up as late as possible, or load up in the middle of the night. SGEM trials of having full storage houses charge the heat storages according to spot price have also been successful.

In the future, when the value of balancing services of heating systems increase with further penetrations of intermittent RES power production, heat storages might not be loaded to the hilt, but according to estimated future demand. The charging function might also be dynamic, allowing the heating system to perform demand response operations as required.

3.3 Electric vehicles

Electric vehicles are insofar interesting that they might well be individual user points in the future. Charging (or discharging) of an EV could be directed directly to the EV and not the physical location even at “home”. However, here it is assumed that charging at home is part of the load of the house and thus affects it. The use of electricity in a car can be estimated using car usage studies as has been done by Koreneff et al. (2009). Further behaviour studies are also done in SGEM, see e.g. Ruska et al. 2010, but also reports by other authors. A lot depends also on the car type, that is, is it a full electric vehicle (FEV) or, for example, a plug-in hybrid electric vehicle (PHEV), and on the mileage per energy input. Figure 7 shows the profile of charging possibilities (day 00-24) for different kinds of electric vehicles.

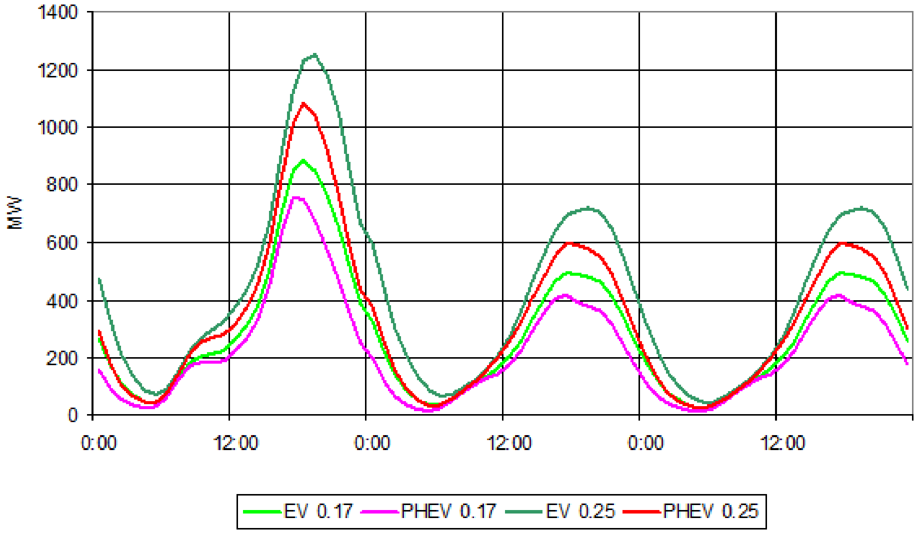

Figure 7. Daily charging profile for one million electric vehicles, of different types, assuming charging begins as soon as cars are plugged in. 0.17 refers to a consumption of 0.17 kWh/km of full EV sedan and 0.25 kWh/km for a sport utility type of full EV. PHEVs use less electricity as they run partly on gasoline. Source: Koreneff et al. 2009

The need for charging the batteries is one thing, how and where it is done is another thing. The charging possibility is defined by when a vehicle is connected and how empty the battery is. As EV's are used in everyday life, especially for driving to work, charging at work is a real possibility. It can also boil down to costs, especially if the charging is gratis or if it is overpriced there. Most of the charging will, however, take place at home at least in the beginning of the EV era. With an increased EV penetration, options, customs and habits might change.

The question of when the vehicle will be charging is also a question of how it is debited. If the price of electricity is directly linked to the spot or time-of-use (ToU) tariff price, and the EV has the ability to automatically steer the charging to the most economic hours (while upholding a adequate charge level). This is smart charging 1.0 versus dumb charging which starts the second the car is plugged in. Smart charging 2.0 is having the car reacting to short warning time system signals, for example the need for up- or down-regulation or for secondary reserves, and smart charging 3.0 would then include vehicle-to-grid (V2G) options. Figure 8 shows an example of a smart charging profile, where charging during the day/evening peak is avoided and postponed to a great extent and night-time charging favoured instead.

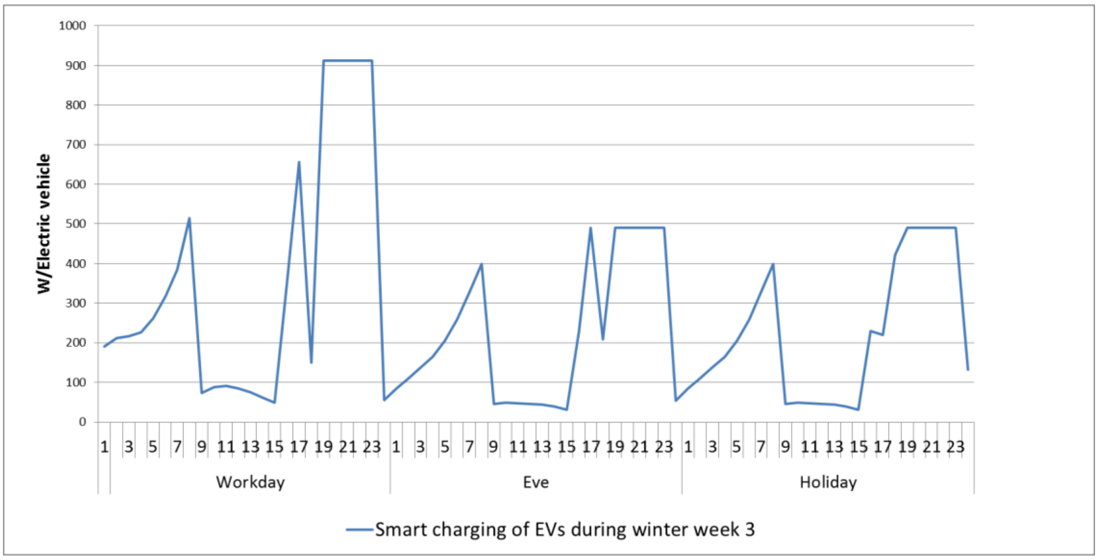

Figure 8. Example of a smart charging 1.0 profile for electric vehicles in the winter. NB.The days here are traditional power utility day 07:00-07:00. Data source: Koreneff et al. 2009.

For the load profile purpose, we need the estimate of dumb charging taking place at the house. From the estimate in Figure 7, we have to extract the charging taking place elsewhere, that is, at work or in public charging places. For ABBA, we do also need an algorithm for displacing the charging to more suitable hours due to either ToU or spot pricing. For BBBA, we would need at least one generic smart charging profile related to ToU tariffs.

3.4 Local power production

3.4.1 Photovoltaics

Solar power has a regular maximum production profile. The variation of the solar maximum irradiance follows daily and seasonal cycles, and local weather conditions such as clouds or rain can reduce it. PV output in turn follows the solar irradiance, but for individual instances the longitude and latitude, the installation angle as well as local shadowing objects have an impact. Air temperature also influences the efficiency of a PV to a degree.

VTT Solar model (Löf et al. 2014) is here used to simulate the production of a 1 kW PV panel using realised solar radiations in Helsinki and Jyväskylä 2014. As can be seen in Figure 9, the wintertime production can reach high, but is mostly quite low due to cloudy weather and short days. The PV production can also be low during the summer, as the production 1.7.2014 shows.

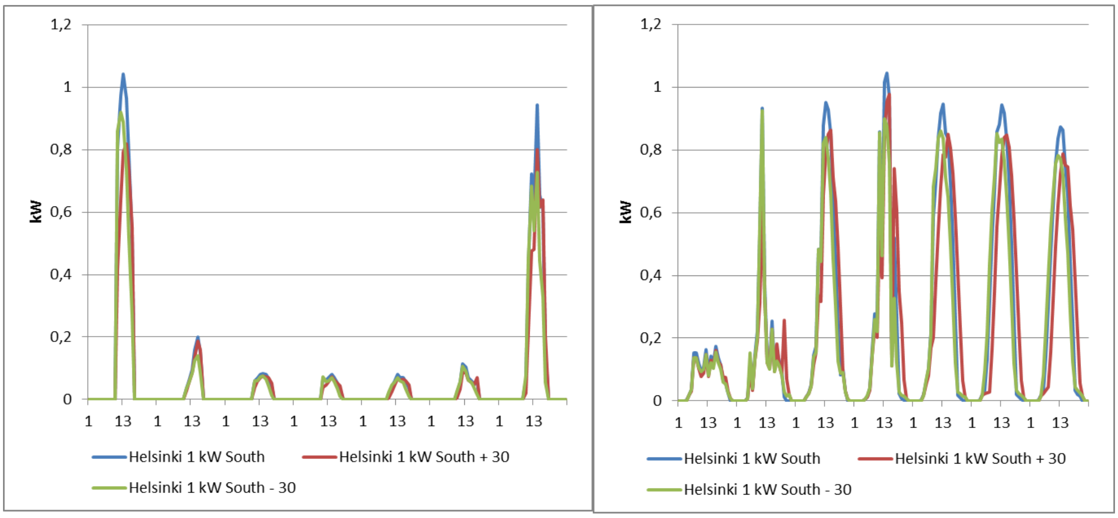

Figure 9. Calculated PV production in Helsinki 23.-29.1.2014 to the left and 1.-7.7.2014 to the right based on measured solar radiations. The PV panel is angled directly or ± °30 south.

Geographical differences can be noted in Figure 10 especially in the summer. The production starts a bit earlier in the South (Helsinki) but remains in turn a bit longer in the North (Jyväskylä). The annual production would have been 100-200 kWh higher in Helsinki than in Jyväskylä 2014.

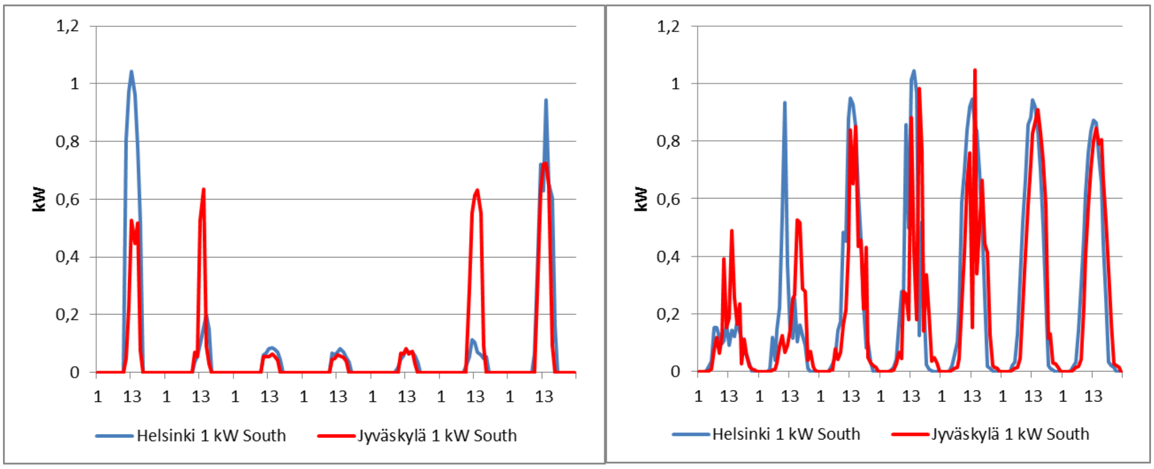

Figure 10. Calculated PV production in Helsinki and Jyväskylä 23.-29.1.2014 to the left and 1.-7.7.2014 to the right based on measured solar radiations. The PV panel is angled directly south.

Solar panels are a hit in Germany, but only thanks to exorbitant feed-in tariffs (FiT). As the investment costs, including installation, PV is beginning to form an alternative even in Finland when the production is used on-site. Summer cottages, connected to the network or not, might be a good candidate, especially if there are EV's in use. In single family or semi-detached houses the loads and the production correlate less well unless there is air conditioning installed. To recognise if a user has a PV installed one of the main indicators is the existence of negative loads. We can assume that there will be some negative load hours even if the PV capacity is targeting own use only. The amplitudes of the negative loads can be used in an assessment of the installed PV capacity when compared to similar loads without PV.

With local weather data and forecasts available, the PV profiles are best made on the fly. As can be seen in Figure 10, the productions vary geographically occasionally quite a lot. For general purposes, profiles can be made by a model using, e.g. five year weather data and assumptions of the distribution of installation angles and shadowing objects. The standard deviations can also be assessed with the same material.

3.4.2 Electricity storages

Net metering is a necessity within the market time unit, that is, one hour at the moment. Any net metering in excess of that, for example per day or per year, does disturb the market operation and does not give any incentives to demand side responses. In the future, batteries may become cost-effective in PV systems and once we have batteries installed, they can also be used for balancing purposes not related to PV per se. In the winter, electricity can be bought during inexpensive hours and stored for use in expensive hours.

Electricity storages are best modelled using heuristic fast algorithms, but they are a question for the more distant future. One way to recognise the existence of electricity storages at single users is by looking at the hourly consumptions during summer afternoons. The existence of a storage can be deduced if there are regular occurrences of zero energy hours.

3.5 Part-load identifications

One of the most difficult tasks in the BBBA approach is the identification of existing part-loads and their profiles, including an assessment of their annual energies. This aspect has been studied in SGEM WT4.3 by Antti Mutanen's load research SGEM team at Tampere University of Technology and Harri Niska at University of Eastern Finland using. With the massive data nowadays available thanks to hourly measurements, part loads are much easier to identify than before. In this report we assess the heuristic evidence that can be found in end-user load measurements. Customer information systems do not always have up-to-date information on the end-user constellations and especially new part-loads such as auxiliary heat pumps, PV, EV might altogether be outside the scope of customer information systems in use.

3.5.1 Household electricity

The annual energy used for household appliances can roughly be estimated at 5 MWh. Household electricity can have a seasonal variation related to lighting or air preheating, but the variations are several decades smaller than for direct electric heat.

3.5.2 Electric heating

Electric heating is very energy consuming, overall, so high annual energies are indicators of direct electric heating. If the size of the house and the construction year are known, minimum annual energies can be estimated. Generic rules are more difficult, as new houses are or will be low-energy houses or even passive houses. There are other indicators as well. As electric heated houses usually have ToU tariffs and heat storages at least for DHW, the end-user load of electric heated shows a clear peak either when the ToU night-time starts or ends. Larger electric storages can be identified by the night-time loads and the absence of heating loads during the mornings and days. Electric heating loads also correlate to outside temperature, a clear indicator.

3.5.3 GSHP

GSHP houses use about one third of the heating energy direct electric heated houses use. If historical annual energies are available, a drop of the heating demand to one third is a clear indicator of the installation of a GSHP. GSHP are probably not installed in low-energy houses, as the specific installation costs for a small system are relative high.

Even if the GSHP capacity is only 50% of the peak demand, meaning that the difference is produced will electric boiler, the peak electric need for heating is only 65% of that of a direct heated house. GSHP are also more steadily in use around the clock and not concentrated to night-time.

3.5.4 AWHP

All outside air heat pumps show weakening COP with sinking temperatures. The temperature regression coefficient can therefore be steeper than in direct electric heating or with GSHP.

3.5.5 EAHP

Exhaust air takes the heat from the ventilation out air, so it is quite stable around the year. At hard colds the ventilation is often halved which results in less heat to be had for EAHP. EAHP, supplemented with electric boilers, can be the main electric heat source in modern low-energy houses. For older and more consuming houses, EAHP are auxiliary heat sources.

3.5.6 AAHP

Air-air heat pumps have no storages and are used as auxiliary systems. An AAHP can be identified, for example, by finding a clear temperature correlation in the high heat days of summer, but the absence of a correlation is not proof of an absence of an AAHP. AAHP's are estimated to decrease the electric heat load by one third, for example 5-7 MWh, although all installations are not as successful.

Modern AAHP's can operate beneficiary up to -25°C.

3.5.7 Solar heat

Solar heat is strongest in the summer and dwindles towards the winter. If the load shows no signs of electric heat in the summer (for DHW) but clear signs in the winter, this can be an implication of solar heat.

The standard deviation can be estimated using weather data and for example the VTT Solar model.

3.5.8 Stoves and fireplaces

Stoves and fireplaces can be identified by seeing that some days have clearly lower electric heat demands than expected, while other days are more on level with the expectations.

3.5.9 PV

One indicator for the existence of PV panels in a house is the existence of negative loads during the day. Another indicator would be a clear dip in daytime loads matching on average an estimated PV production profile.

The standard deviation of PV profiles can be estimated using weather data and for example the VTT Solar model.

3.5.10 Micro-CHP

Micro-CHP's can be run against the heat load, the electricity demand or according to what is economically wise. Our test runs in SGEM with micro-CHP operation model show that running a micro-CHP, usually equipped with a small heat storage, against the electricity demand is the most unoptimal solution even in countries having high electricity prices not to even mention Finland. If we operate the micro-CHP against the heat demand, it is entirely possible that negative loads exist in the heating season. Anyway, independent of operation mode, net electricity demand will be low.

3.5.11 EV

Electric vehicles need a lot of electricity, but charging will mostly be restricted by the fuse size, so load shifts of roughly 2200 W (10 A) or 3500 W (16 A) taking several hours can be signs of EV's. If there are more EV's at a house, will they have sequential charging or parallel, and will their charge demands differ? EV vehicles are the more profitable the more they are used, it can be assumed that EV's are used as everyday cars, not as reserve cars, so we can assume that the charging demand is similar.

3.5.12 Electric saunas

Electric saunas are quite common in Finnish households. Their typical time of use is in the evenings. As they are large loads, several kilowatts, they can form typical Friday or Saturday evening peaks, especially if their use also affect DHW heating needs. Saunas also heat the house, which in turn can decrease the demand for direct electric heating or, in the summer, increase the demand for cooling.

3.5.13 COP

The performance coefficient of heat pumps, especially for ABBA use, can be modelled. Of course, heat pumps evolve and future heat pumps are expected to have a better COP than nowadays pumps. The development can, however, be estimated and estimates can be found in the literature (see for example EC JRC 2014).

3.6 ABBA model

A computer prototype of the intricacies of an ABBA type model was put up, where such operators as addition, max selection, and multiplication were implemented together with time series and profiles for the estimation of the load of a house.

The target is to add also algorithm functionality in the future, making it generic tool for the testing of both static and dynamic profiles.

Confidence intervals, standard deviations etc. are not implemented yet. The expected range of the load cannot be calculated merely as before, as storages for example can have a higher uncertainty in the timely direction than of the amplitude.

4. Summary and conclusions

The idea of simulating household loads using part-load building blocks instead of just one single profile is brought forth as a solution to the ever more increasing complexities of modern household loads.

We have different kinds of heat pumps at our disposal, both for use as main heat sources but also as auxiliary heat source. Solar solutions such as thermal or PV panels are becoming more cost efficient and may be competitive in one or two decades. Electric vehicles show great promise as one solution for a carbon-free future.

These all have large impacts on the loads of a house. At the same time, the part-loads can be orthogonal to each other, having very different explaining factors to their behaviour. The main idea of this report is to in the basic building blocks approach (BBBA), where we use part-load profiles in the same way as traditional profiles are used, with the exception that one user can have several of them, and some of these part-load profiles can be negative.

With a few new profiles, for example the electricity saving profile of an air-air heat pump in an electric heated house can bring us a long way for starters. Then we need a PV profile and probably also a couple of electricity saving solar thermal profiles. We need two profiles because the electricity saving is different in a direct electric heated house than in a ground source heat pump heated house. Then we need a couple of electric vehicle charging profiles to get the starter pack complete.

These part-load profiles can to a great deal be formed using the SGEM research results at hand. The practical problem lies in the identification of a user’s part-loads and to estimate the annual energies linked to them. Existing customer information systems won’t be much of assistance as they maybe have no slots for PV, EV etc. or the data they have is not so reliable anymore. For example, customers seldom inform the utility of heat pump installations or other heating system changes.

For a more advanced building block approach (ABBA), part-loads profiles are more and more algorithm based, locally oriented and weather sensitive. Whereas generic profiles are more static, in the ABBA approach we get closer to household specific profiles and balance/state calculations. Still, one of challenges will be to estimate the sizes of the part-loads. First steps to a heuristic based solution are presented in this report. These can be combined with automated clustering based results as well as neural network etc. different techniques to meet the minimum requirements for using part-load building blocks.

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