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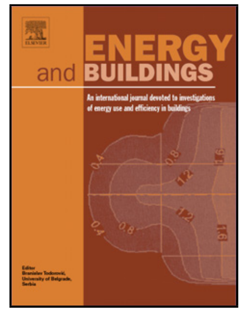

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The Generation of Domestic Hot Water Load Profiles in Swiss Residential Buildings through Statistical Predictions

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Abstract

A long-term field study recording domestic hot water (DHW) consumption in households was used to tune a load profile generator. The methodology used in this load profile generator is also applicable to electric loads in distribution grids. Accurate DHW load profiles are essential to estimate the performance of renewable energy systems. One day and long-term randomly generated DHW profiles are useful for simulation, sizing and optimization of components in solar hot water installations such as storage tank, heat exchanger, collector area and additional heater. This work is also relevant to create standards for product testing and certification.

DHW usage and draw off patterns are geographically dependent, so recent and local measurements are required to tune models and create accurate load profiles.

Measurements show that DHW consumption is very volatile. The daily average value varies from 20 to 40 Litres per person (60 °C outlet temperature). The profiles underlie some trends (predominantly consumption in the morning or in the evening or spread over the day). The DHW consumption in Switzerland follows similar patterns observed in other countries, such as no significant decrease in

consumption during weekends, and no strong correlation with weather conditions neither outdoor temperature nor rain.

Keywords: DHW, Heat demands, Consumption Profiles, Demand modeling, Survey

1. Introduction

The heating of domestic water for bathing, washing, cleaning and other domestic uses contributes significantly to the energy bill and use of natural resources in the residential sector. The Domestic Hot Water (DHW) usage and habits of modern users are not well investigated. There are some guidelines that estimates the water flows through components such as boilers and heaters [1], [2]. Construction guidelines were written in a context with less greenhouse effect awareness and low energy prices. Fossil-fuel based technologies such as gas or oil heating boilers can react almost immediately to DHW demand because fuel is steadily available. This is not the case for solar radiation where storage tanks or backup systems are required to match the demand. When predicting the performance of renewable energy systems in domestic hot water applications, accurate load profiles are essential. For example, DHW use in the afternoon are more easily covered by a solar thermal system due to the daytime charging by the solar collectors.

Reliable DHW use profiles are of great importance to find the optimal heating strategy for each application [3-5] and to optimize the components of DHW systems. They are also useful to design tests for the components, with data such as number of draw offs per day and average resting times useful to evaluate fatigue, deposits, compare performance and control strategies under comparable conditions. There are several national standards that give DHW averages and distribution profiles [2], [6-8], in public buildings [9] and some studies that update these values [10-13]. Table 1 shows some reference average DHW consumptions for different regions.

There are similarities in how to obtain DHW and residential electric load curves. The mathematical models are almost identical. There are two main methodologies, the so called Top-down and the

Bottom-up models [14]. In the Bottom-up models, the demand of each load is taken into account and the total load curve is obtained adding all the individual consumptions together. Bottom-up models are not very common for DHW. The models predicts the consumption of each device and sum them up, so data from measurements at each individual terminal is required to validate the models. There is available data of consumption patterns to build accurate electric demand models [15], but draw off data is more complex to obtain. Each electric appliance has a specific use, so the electric power measurement of a TV-set or an oven gives a good estimation of the occupants' consumption patterns for each activity. The measurement point of hot water draw offs is not related to the activity. There are only three or four hot water faucets in a dwelling but there are a dozen of activities (water use) with random events, so measurement data can not provide information to predict frequency and consumption for hand washing, dish washing, cleaning or toothbrush. There are acknowledged methods to generate DHW draw profiles based on Bottom-up methods [16] but there are not as detailed as models for electric consumption where pattern recognition models can be used to identify activities. Top-down methods aim to obtain information from aggregated data [17]. These methods aim to find trends and patterns from DHW consumption profiles without identifying the activities.

DHW consumption have geographical variations that are influenced by climate, habits, environmental concerns and socioeconomic status. Also, there is a historical trend of DHW savings in the last decades [5], [18], so the models have to be adapted to the region and periodically updated. There are some common factors that have been observed such as outdoor temperature and weekend vs. working day. But these factors are local, as the DHW consumption increases in hot days in some regions (New York), but reduces in others (Florida). The differences are also noticeable in the daily profile: consumption in Finland in higher at evening and lower during morning whereas this behaviour is opposite in Germany [10]. Models become more accurate if several parameters are added such as age and occupation are included [19].

Heat pump are gaining popularity for DHW and heating [20]. The ratio of useful heat per electric energy is up to four times. Heat pumps become a connection point between the electric grid and a thermal system with high inertia. At present, there is no cost-effective technology to store electricity in the distribution system, so the interconnection is an opportunity for grid regulation and peak shaving. Heat pumps can be disconnected for short periods of time without loss of comfort and their performance for demand response is under investigation [21].

DHW data from Switzerland are very scarce. Moreover, Switzerland is a very cultural diverse country and it could be argued that the German, French and Italian speaking regions may present local variations in the DHW consumption patterns. The data presented in this paper were collected exclusively from German speaking regions and from multi-storey residential buildings with average 6-8 dwellings per building that are common in this area.

The paper presents the result from one year DHW measurements in four dwellings and the parameters extracted from this measurements to create DHW load profiles. Average values and distribution functions are sufficient for component sizing of solar heating systems. High resolution profiles are of interest for laboratory testing of equipment and certification, among others. The information is presented as following: Section 2 presents a method to create time series of randomly generated DHW load profiles. Section 3 present data from the DHW consumption measured during a whole year in 4 dwellings. Section 4 presents an example of a representative DHW load profiles obtain with the method in section 2. Section 5 discusses the parameters that influence DHW.

2. Method

2.1. Measurement data

Recently a long-term study measuring DHW profiles in Switzerland has been completed. The DHW use profile was recorded during a whole year. Four different dwellings were selected for this paper from residential multi-story buildings, very common in Switzerland. These constructions have an average of 6-8 dwellings per building and were erected in the sixties resp. in the nineties. These dwellings are all equipped with decentral storage tank water heaters with resistance heating element and are subjected to be replaced in a near future because of their poor energy performance. The energy metering system includes the temperature of intake water, and of the hot water leaving the storage and the water flow rate as presented in Fig. 1. Flow meter used in this study is a Unico from GWF MessSysteme AG, rated with an accuracy class 3. The flow sensor adds the water used and sends a signal for each accumulated 0.25 l. The cold water intake temperature was measured with PT100 sensors. The thermal energy content of the water is computed by software. The readings L_{nl} are expressed in standard liters of hot water with a starting temperature of 10 °C and final temperature of 60°C, as expressed in eq. 1 [5], [10] and [11]:

$$L_{nl} = L_{measured} \cdot \frac{(T_{hot} - T_{cold})}{(60° - 10°)} \quad (1)$$

Where T_{hot}, T_{cold}, and $L_{measured}$ are the measured outlet and inlet temperature of the storage tank and the water used. The measurement device adds up and sends the measurements in steps of 0.25 l, meaning that the last drops of a water draw are accounted in the next draw. The error for each measurement is ± 0.25 liters, but this error does not sum up for the total daily consumption. The error in the daily DHW average becomes 0.25 ± 3%. Some of the dwelling's parameters are presented in Some days registered zero DHW consumption. The days when the occupants are not in the dwellings where not considered for this study. The average consumptions presented in this study are therefore slightly higher than average considering the whole year, as the days without consumption are not representative in the load profiles.

2.2 High resolution DWH profiles

The authors are interested to find a representative one day DHW draw profile at high temporal resolution to be used as a reference in system simulations and equipment lab testing. Random profiles for long term simulations are also of great interest. The International Energy Agency's (IEA) Solar Heating and Cooling (SHC) Programme Task 26 presented a well stablished method to create long term DHW profiles [16]. This method assumes that the water draws come from four different categories. The categories are determined by the average water draw and not by the use or activity. Draw offs with 1 liter in average correspond to category A, 6 liters correspond to category B, 140 liters to category C and 40 liters to category D. The amount of water at each draw follows a Gauss-Distribution with a given mean and average for each category. The method requires also a known Probability Distribution Function (PDF) of the DHW-load in the course of the day for each activity. Fig. 2 shows the load profile of 24 hour data with a one minute resolution generated with this method. Fig. 3 shows the flowchart explaining how the program works.

There are a number of statistic parameters required to generate time series of draw profiles. Some of them are found in literature, such as hot water consumption average and distribution. Other parameters, such as number of activities, average draw per activity, number of events (i.e. draws) per activity and per day and statistical distribution of draws, are very specific and there is not sufficiently available information.

Measurement data from four dwellings in Switzerland were used in this prospect. The probability distribution functions of draw off activities required to build the DHW profiles have been calculated for the selected four apartments.

3. Water-use analysis

3.1. Measurement data

Mean and variance are the usual parameters to present the daily consumptions, assuming a normal distribution. Data collected from the four dwellings was used in the Kolmogorov–Smirnov test to determine if the normal distribution assumption is correct [22]. Fig. 4 shows the daily consumption during a whole year for working days sorted from lower to higher for each dwelling, that match the characteristic shape of normal distribution functions. Not all dwellings have the same number of data points as days without consumption are removed, and occupants took a different number of vacation days. Three out of four showed a p-value with a significance level of the test over 99.7%, and all of them rejects the null hypothesis of the Kolmogorov–Smirnov at the 5% significance level, so the normal distribution seems like a good approximation for the daily consumption as all four dwellings.

Mean and variance of DHW consumption of the four dwellings are presented in Table . Some studies discussed the difference in consumption of working and weekend days, so the data is presented separately, although no statistical significance was found. Also, the consumption in rainy days has also been investigated.

3.2. Number of activities

A random generator of DHW load profiles requires an average number of draw offs and an average liters per draw, assuming again a normal distribution. The method presented in [16] suggests four categories with given average number of draw offs per day, an average duration of each draw and normal deviations for each parameter. One category suggested has an occurrence of only once a week and it is only of interest for very long time series. Fig. 5 shows the histogram of draw offs for an entire year in dwelling number 2.

The analysis of the data shows that more than four categories are required to fit the draw offs into normal distribution functions. Categories lose the physical meaning if more categories than facets or activities are used. In this study, the data is presented in three different categories, in accordance with [23] and [24]; the definition of the categories is presented in Table 4.

It has to be noted that the measurement data shows that the consumption for each activity does not follow any known distribution function. The generated load profiles will be distinguishable from measurement data if long time series are analysed.

The draw offs measured during a whole year have been sorted according to three activities and the results are presented in Table 5. The input data were collected for a whole year from July 2014 to June 2015 with a resolution of 0.25 l.

3.3. Probability distribution function

The pdf of the DHW for each activity is found with a Kernel Smoothing function. The average consumption in liters per hour is obtained multiplying the pdf with the mean consumption. Fig. 6 shows the average consumption for the 4 dwellings separated between working days and weekends, as well as for activities. The figures were built with data from a whole year.

4. Load profile generation

The procedure to create a randomly generated one day load profile or long time data series is very similar. An example of a one day load profile with the method presented in [16] is developed in this section. The parameters required to generate random load profiles have been obtained from measurement data as discussed in section 3. The dwellings studied were selected after a statistical analysis to represent the average consumption for the targeted population. The PDFs of the DHW load consumption shows great variability between the dwellings as presented in Fig. 6 The standard deviation of the daily mean consumption is also high.

It is important to notice the effects of the simplifications introduced in the method. The draw offs do not follow any simple statistical function, and the normal distribution is just an approximation. The difference between randomly generated and measurement data can be observed if aggregated data is studied, but a single day profile is not distinguishable. Also, normal distributions may give negative values. Negative draw offs are not physically possible, so negative values should be removed from the model.

It has been shown that the daily DHW consumption has great variability, up to four times higher from the lower to the maximum consumption day. A one day representative load profile would be of great to make a standard test procedure, but the authors argue that this is not enough to realistically replicate the stresses and requirements of the components. Instead, two or three one day load profiles, one for a low consumption day, one medium and one for a high consumption use would replicate more realistically the operation conditions. As an example, a load profile of a dwelling with 5 people and an average of 40 liters per person is presented (200 liters).

For the purpose of this project, dwelling #2 was selected in terms of pdf to create the reference profiles. The same PDF may be used to create low, medium or high consumption reference profiles. The average number of events per day and the mean consumption per activity presented in Table 7 are used to generate a random profile. All randomly generated profile are statistically possible but some random generated profiles may have all the consumption concentrated in the morning or in the evening. This variety of profiles is also found in experimental data and it is useful when long time load profiles are required, but some extreme values are not interesting for a representative one day load profile. It is desirable that the one-day profile mirrors some average parameters, so a number of arbitrary criteria are introduced to automatically evaluate the randomly generated load profiles. The profile is accepted if fulfils the requirements; if not, a new profile was generated. This filter ensures that the draw offs are well distributed during the day. The criteria for acceptance is:

- The total water consumption is ±5% of the aimed amount.
- At least one activity 3 event for the middle and high consumption profiles
- Not more than 30% of the draw happens at night.

A five day randomly generated load profiles is presented as an example in Fig. 7. Note that the first day has an early draw off of 86 liters. This profile falls out of the algorithm criteria and it is not selected for a representative load profile, although some real load profiles may look very similar. The loads are presented as instantaneous draw offs of hot water. A realistic load profile is not formed with discrete events. A standardised volume flow rate is assigned to each event and each draw off is extended to the corresponding duration. As a result, the load profile is smoothed. The flow rate for each activity is presented in Table 8. The last day passed the requirement criteria and is selected as the representative one day load profile. The flow rate is then limited by the values at Table 8 and draw offs are spread over several minutes. Fig. 8 presents the resultant representative load profile.

5. Discussion

The data analysis of the 4 dwellings in Switzerland showed similar trends found in other locations and some specific information that may be extrapolated to other locations. For example, the average DHW consumption (37.44 liters per person from Table 3) is in line with other European studies and lower than in USA and Canada (see Table 1). The generated one day load profile was constructed with 40 liters per person to be representative for European dwelling. Some findings that deserve further discussion include:

5.1. Weekends and working days

It was pointed out that the average consumption was slightly lower during weekends in previous studies in Finland [10] and Hungary [11]. This discrepancy has also been observed in our study (see table 3), but it was not strong enough to find statistically significance. The most relevant difference between these two categories is the load profiles, with later morning peaks in weekends.

5.2. Seasoning and temperature

Some authors discussed the correlation between DHW and seasons or outdoor temperature [4], [10]. The correlation between temperature and DHW consumption is very low and not statistically significant for the analysed dwellings. This finding is in line with previous studies. Fig. 9 presents the DHW consumption per day sorted by the day's maximum temperature and the linear regression line for dwelling number 2. The regression parameter β is 0.116 liters less per temperature degree, but it is clearly not statistically significant based on the variability.

5.3. Rainy day

Rainy days are also related to weather seasons and temperature, so the influence of rain is indirectly covered in previous studies. Authors did not find previous studies specifically on the influence of rain in the hot water consumption habits. The average DHW for days with at least 1 mm of rain and the overall average is presented in Table 3. Other thresholds were also tested to differentiate from low and heavy rain, for example days with over 5 mm of registered rain, and no statistically significance between rain and DHW was found.

5.4. Day before correlation

The hot water consumption in the higher consumption days is in the order of 4 times higher than in low consumption days (excluding vacation days with no consumption at all). It could be expected low consumption after a high consumption day but no correlation was found. Fig. 10 presents the DHW consumption per day at dwelling 2 in chronological order. The consumption do not follow any predictable pattern.

6. Conclusions

Detailed data from the hot water consumption patterns of four typical dwellings in Switzerland have been presented and processed to generate consistent DHW load profiles. The data were collected for a whole year from July 2014 to June 2015 with a resolution of 0.25 l. The dwellings were selected as representative of the multi-story apartment buildings built in the 1960s and 1990s with around 8 dwellings per house common in Switzerland. This data updates the DHW consumption behaviour, useful for sizing and optimizing components such as boilers, heaters and solar panels.

The data presented in table 5 includes average number of water draw offs per activity and probability distribution functions required to generate high resolution and long-time series of hot water load profiles. An example of a randomly generated one-day load profiles were discussed. Representative reference load profiles are of interest to test hardware components, compare performance, control strategies and benchmarking under same conditions.

Parameters that affect DHW have been investigated. Switzerland households follows similar patterns observed in other countries, such as no significant decrease in consumption neither during weekends nor correlation with temperature.

Acknowledgements

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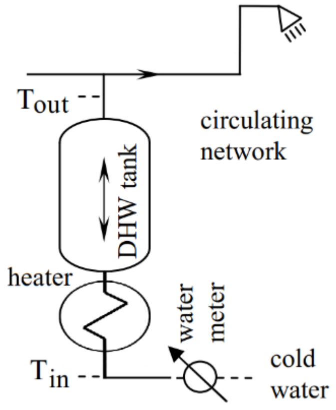

Fig. 1. Scheme of the DHW system and the measurement system.

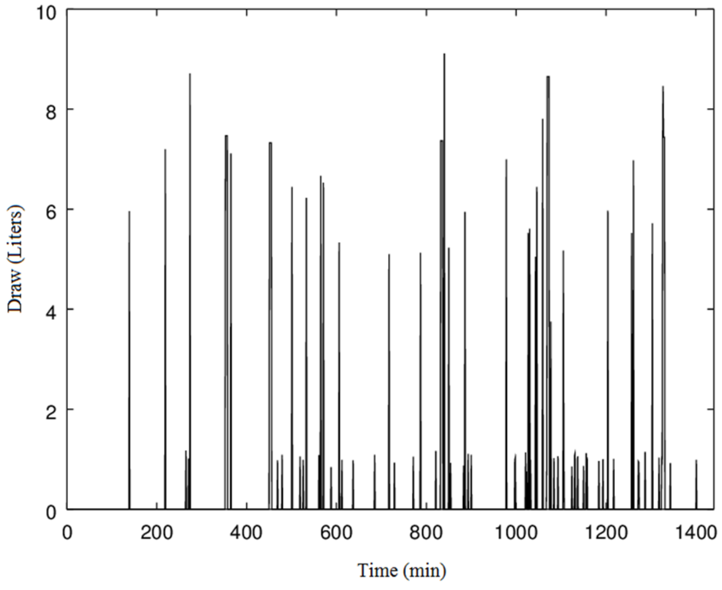

Fig. 2. Example of a load profile of 24 hour data with a one minute resolution randomly generated with the method presented in [16].

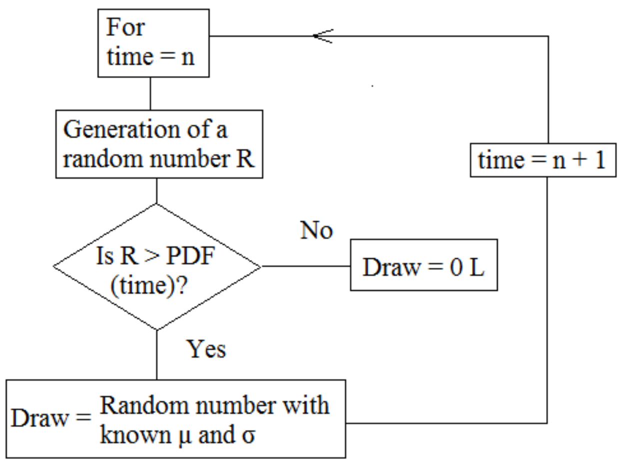

Fig. 3. Flowchart with the implementation of the [16] method for load profile generation. The amount of liters in each draw off follows a normal distribution with an average μ and a standard deviation σ.

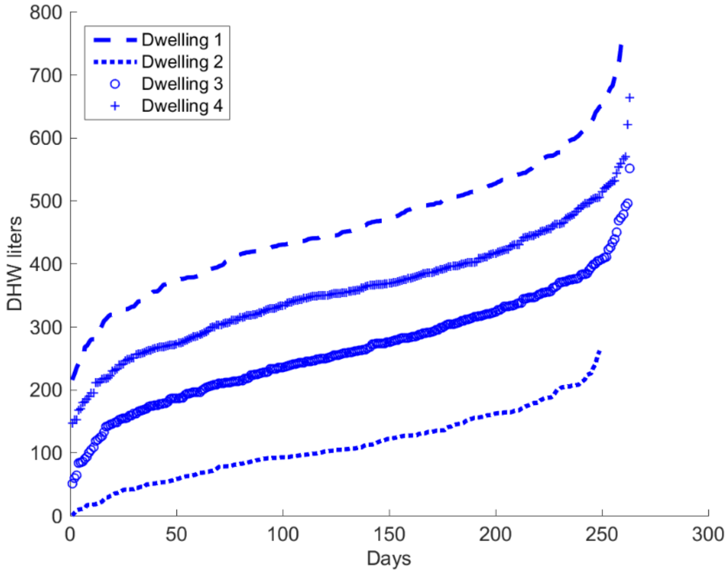

Fig. 4. Daily consumption during a whole year for working days shorted from lower to higher for each dwelling, showing that the DHW consumption follows a normal distribution. Not all dwellings have the same number of data points as days without consumption are removed.

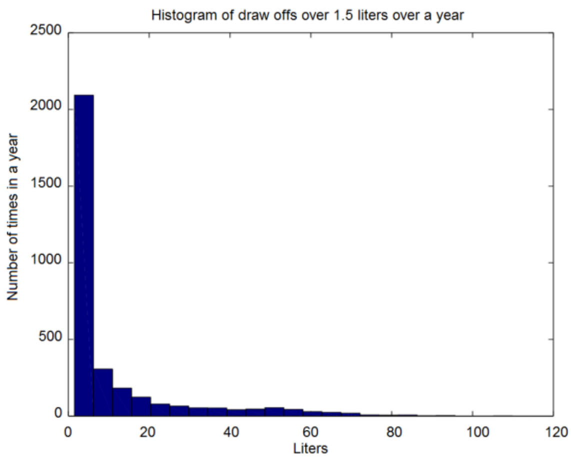

Fig. 5. Histogram of the water used per draw in dwelling number 2. There are 3293 draws with less than 1.5 liters and 3251 with more. A large number of activities with very few events is obtained if the data is fitted into normal distribution functions. In the other hand, if the draw offs are sorted in only 3 or 4 categories, the activities do not follow a normal distribution.

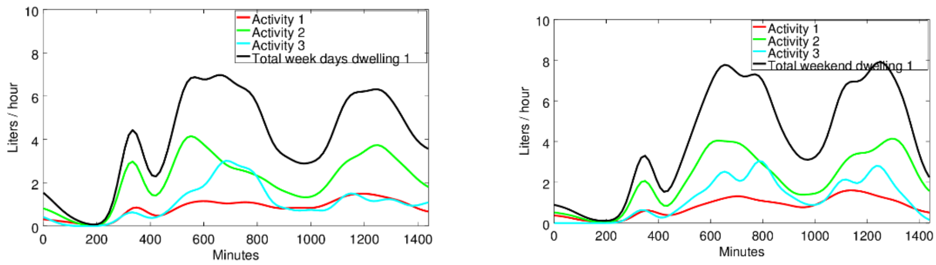

Fig. 6.a- Daily hot water consumption profile for the dwelling number 1 sorted according working days and weekends, as well as for activities. (Profile trend is spread across the day)

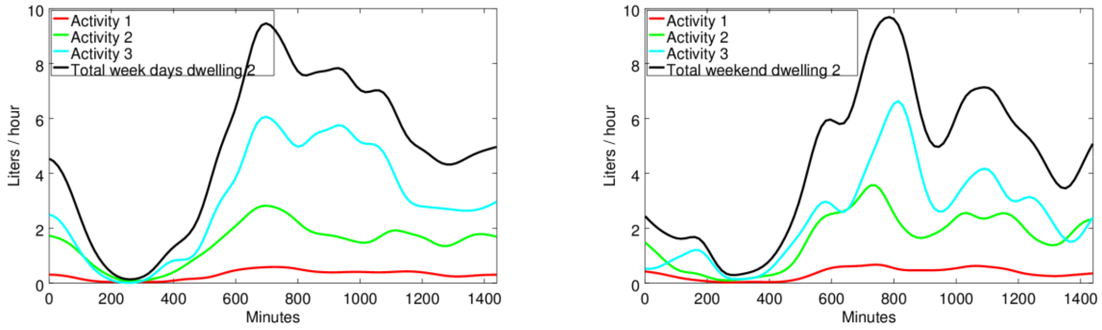

Fig. 6.b- Daily hot water consumption profile for the dwelling 2 sorted by working days and weekends, as well as by activities. (Profile trend is spread across the day)

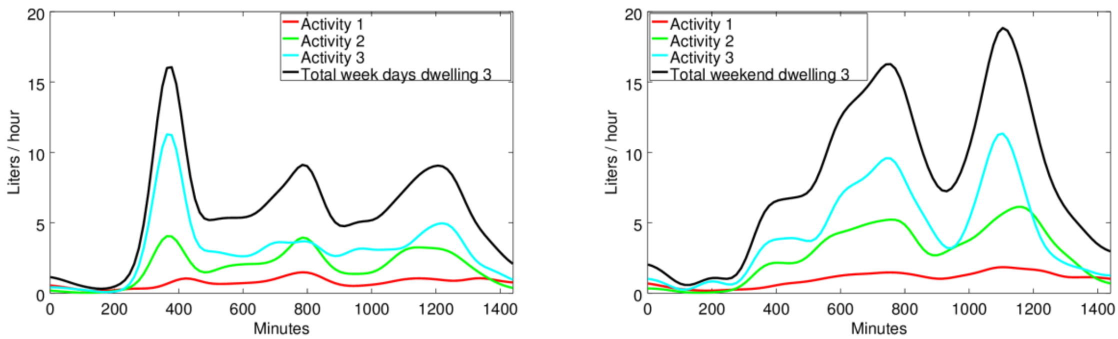

Fig. 6.c- Daily hot water consumption profile for the dwelling number 3 sorted according working days and weekends, as well as for activities. (Profile trend on week day is predominantly in the morning)

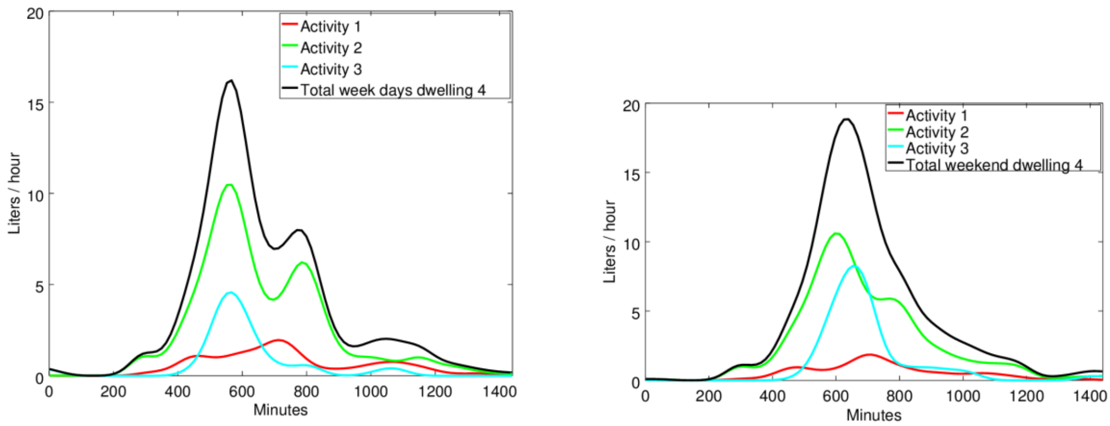

Fig. 6.d- Daily hot water consumption profile for the dwelling number 4 sorted according working days and weekends, as well as for activities. (Profile trend on week day is predominantly in the morning)

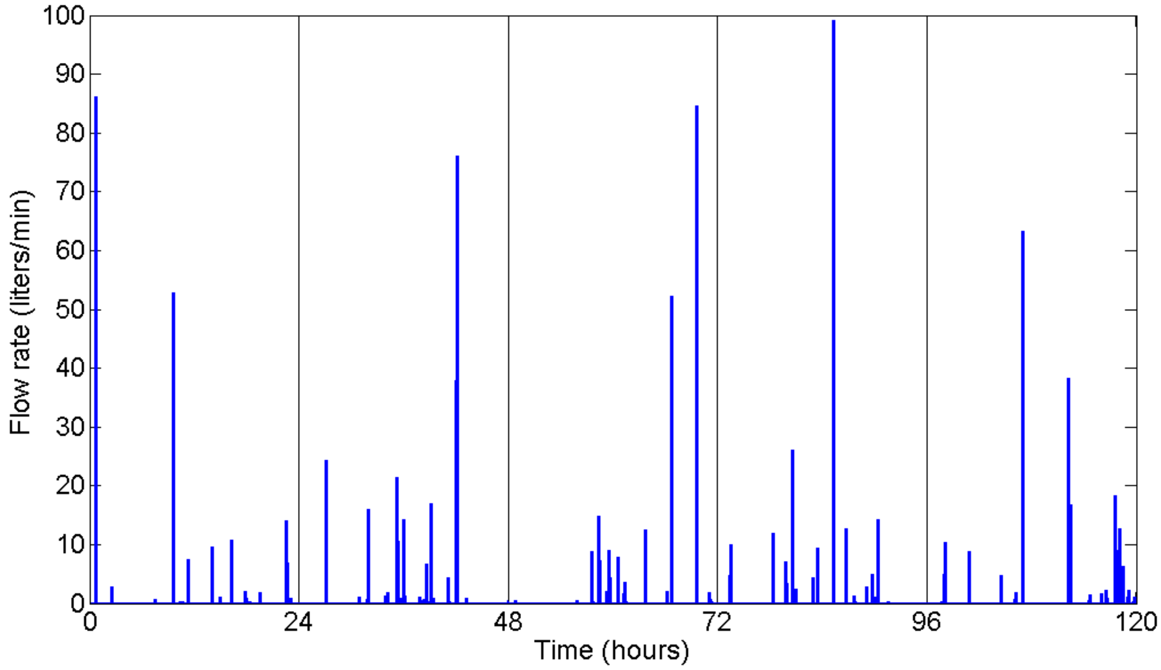

Fig. 7. A five day load profile generated with the method proposed. All days correspond to middle consumption loads to illustrate spread results obtained with the same PDF even when the volume is forced at 200 liters.

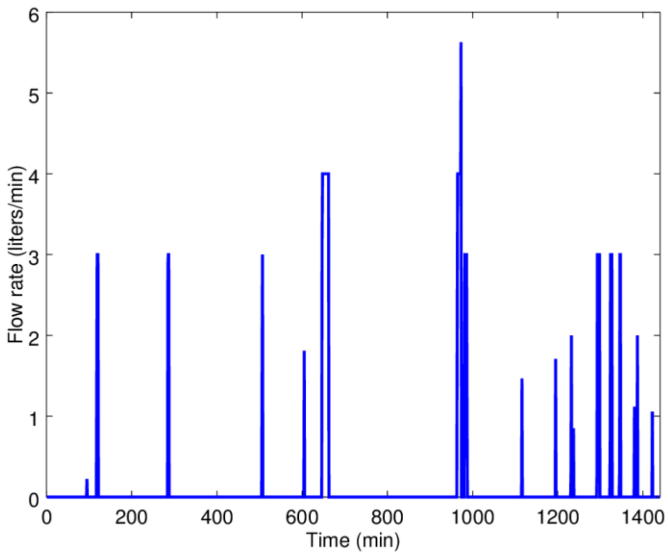

Fig. 8. The randomly generated one day representative load profile. It corresponds to the last day of the load profile presented in Fig. 7 after limiting the flow rates according to Table 8.

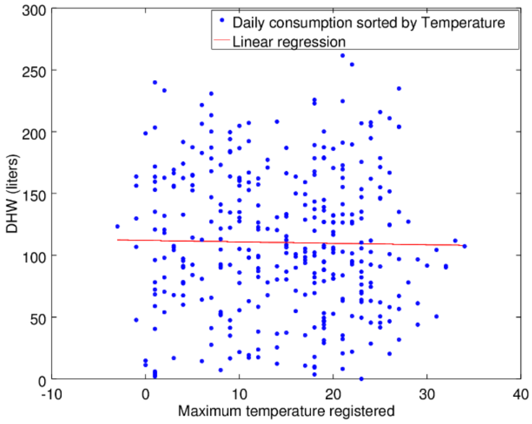

Fig. 9. DHW consumption per day sorted by the day's maximum temperature and the linear regression line for dwelling number 2.

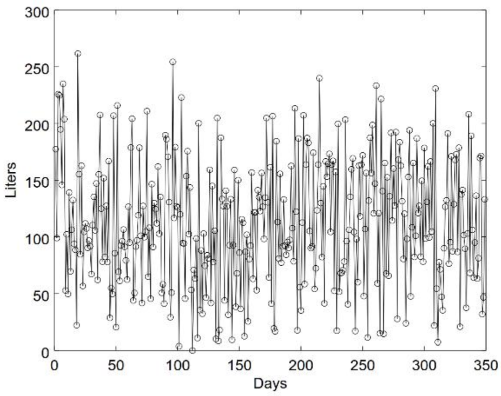

Fig. 10. DHW consumption per day in dwelling number 2. The correlation between high and low consumption days has been investigated. No "storage effect" has been found, and high consumption days are not followed by lower consumption the day after.

Table 1.

Average DHW consumption found in several studies

Region	Average (l/day)	(Year of study) and Notes	Ref
Budapest, Hungary	194,4	(2005) Average per apartment.	[11], [13]
Toronto, Canada	239	(1985) average for household with 2 adults and 2 children.	[7]
Florida, USA	256	(1988) average for household with 2 adults and 2 children	[7]
Ontario, Canada	236	(2003) 2 - 5 occupant per households, with 47 l to 86 l per person depending on the number of occupants.	[4]
North America	239	(1990) average per residence	[4]
Canada	208	(2011) average per residence, with 67 l/person	[4]
Finland	43	(2015) liters per person.	[10]

Table 2

Parameters of investigated dwellings

Apartment number	Number of adults	Number of children	Tank Size (Liters)
1	2	-	300
2	4	1	210
3	4	-	300
4	2	-	300

Table 3

DHW use in the four dwellings

	Flat 1	**Flat 2**	**Flat 3**	**Flat 4**
Average at working days (l/d)	97	114	138.6	87.6
Standard deviation (l/d)	46.3	56.5	58.3	26.9
Average at weekends (l/d)	101.4	106.9	198.8	103.4
Average at rainy days (>1 mm of rain) (l/d)	96.2	106.5	162.1	93.8
Liters per person / day on working days (l/(pers.d))	48.49	22.82	34.66	43.78

Table 4

Volume intervals for each draw off activity

Activity 1 (hand washing)	0-2 l/draw
Activity 2 (long draw, taking shower)	2-20 l/draw
Activity 3 (bathing)	> 20 l/draw

Table 5

Statistical parameters describing the DHW use sorted by activity for each analysed dwelling

	Flat 1	**Flat 2**	**Flat 3**	**Flat 4**
Number of events per day Activity 1 on working days (-)	24.5	10.3	26.5	20.7
Mean and standard deviation, activity 1	0.81-0.51	0.72-0.53	0.69-0.49	0.66-0.48
Number of events per day Activity 2 on working days (-)	10.9	6.24	8.46	10.3
Mean and standard deviation, activity 2	4.72-3.26	5.57-4.32	5.41-3.74	5.757-4.13
Number of events per day Activity 3 on working days (-)	0.656	1.64	1.66	0.53
Mean and standard deviation, activity 3	39.68-20.59	43.6-17.72	46.5-24.25	31.34-13.04

Table 7
Characteristic parameters of the dwelling #2 used for the high-user DHW profile

Number of events Activity 1	10.3
Total draw Activity 1	7.5 liters / day
Number of events Activity 2	6.24
Total draw Activity 2	34.8 liters / day
Number of events Activity 3	1.64
Total draw Activity 3	71.5 liters / day

Table 8
Standardised DHW volume flow rate (in accordance with [1])

	Activity 1	Activity 2	Activity 3
liters/min	2	3	4