SIMLULATION OF DOMESTIC ELECTRICITY LOAD PROFILE BY MULTIPLE GAUSSIAN DISTRIBUTION

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ABSTRACT

The drive towards smart grid and distributed renewable generation in residential areas has impacted on planning and management by Distribution Network Operators. This has prompted the need for improved flexibility in modelling of domestic electric load profiles, to enable replication of important features of real household loads. This paper presents a method to estimate a domestic household's hourly electricity load profile from its daily electricity consumption. Multiple Gaussian distributions are used to reduce and simplify the data requirements for modelling. By discovering the relationship between domestic load profile characteristics and Gaussian distribution parameter, the model only requires six data input, such as number of rooms, to generate a household's hourly electricity load profile. The simplicity of this method made it possible to generate the hourly load profile without the detailed statistical data from the household required by other published methods. A regional electricity load profile can be generated by combining the appropriate number of each household type in the area. The proposed method is tested by simulating and analysing the five groups of domestic load profile. The model and results from this study can be further used for domestic renewable energy system design, zero carbon house planning, domestic energy saving, renewable energy policy making, etc

Keywords: power systems, domestic energy consumption; load profile, renewable energy, energy saving.

1. INTRODUCTION

The domestic sector was responsible for about 30 % of total UK energy use and 27% of carbon dioxide emissions on an end-user basis [1]. Understanding individual domestic electric load profile is one of the prerequisites in renewable generation system planning. Detailed load profiles for domestic electricity use are important as input to simulations of small-scale energy systems, such as micro-grid, distributed energy generation and solar heating. Planners of regional domestic energy supplies and policy makers will also benefit from the study of individual domestic electric load profile, reducing the complexity of the modelling process will benefit both sectors.

A number of domestic electricity load profile studies have been based on a bottom-up approach. In general the bottom-up approach divides a household into many energy consumption units, e.g. kettles, televisions and freezers. The working status of each unit will be determined by the pattern of use of each element by individual family members in a household [3]. The load profile of a household is obtained by summing the energy used at specific time periods for all the energy consuming units. The accuracy of the results is highly dependent on the availability of grass-root level consumption details. Capasso's modelling work described an ideal situation where the stock of appliances and details of their usage patterns in households are known and details about the composition of the load are available [2]. Paatero and Lund also discussed the benefit from knowing both grass root level consumption details and details on statistical averages of energy consumed by domestic users [3]. Yao and Steemers also demonstrated that the load profile of a household depends very much on the occupancy pattern [4]. The above three bottom-up approaches all require larger amounts of grass root level consumption data.

A combined Markov-chain and Bottom-up approach has been used by both Richardson and Widén [5-6]. This method uses national statistical Time Use Survey (TUS) data to simulate the occupancy pattern in a household. By using TUS this approach has reduced the data requirement compared with other Bottom-up approaches. The approach in [5-6] also benefits from the ten minute time resolution of the TUS data to produce a "high-resolution" electricity demand simulation. The ability of this approach to forecast accurately is very much dependent on the availability of the detailed TUS national statistics. This makes it less suitable for use in many developing countries and remote regions where TUS is not available.

A major challenge in modelling of domestic electricity load profile is to obtain detailed data on grass-root consumption for a given household and its occupants. The complexity of data requirement has limited the implementation of the existing approaches. An ideal model would require limited amounts of data to be collected from consumers and avoid the use of data related to technical specifications of the appliances, such as their power rating and efficiency, etc.

Unlike hourly load profiles which depend on consumer occupancy and activity level, daily electricity consumption over a long period of time is often dependent on external variables that typically follow similar patterns over successive years, such as the mean outside temperature and daily daylight hours [3]. The domestic daily electricity consumption could be directly obtained from household monthly/seasonal energy bills.

This paper presents a novel method to quickly estimate the hourly load profile of a domestic home via a Gaussian function approach and electricity load profile of a region via amalgamation of Gaussian distributions. These distributions represent the typical hourly demand profiles of various domestic inhabitants. By representing each type of domestic load profile characteristics using the sum of multiple Gaussian distributions, the model only requires six input data to generate a region's household hourly electricity load profile.

2. THE PROPOSED METHODOLOGY

2.1 Domestic Hourly Electricity Load Profile Characteristics

In order to model the daily electricity consumption of a household on an hourly basis, it is essential to identify the characteristics of a domestic electricity load profile. The domestic load profile can be divided into four time periods as follows: morning peak load period, evening peak load period, mid-day load period and mid-night load period. Those four time periods are shown in Figure 1.

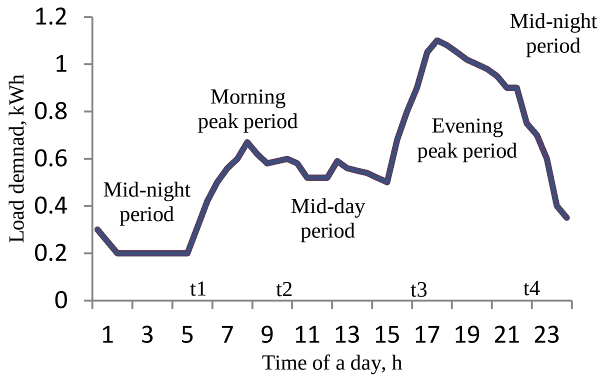

Fig 1: Domestic hourly load profile from National Load Research with marking of four time period [4]. Additional indication of times t1 to t4, where t1: first person wakens up ; t2: last person going to work; t3 first person getting back home ; and t4 last person going to bed.

The morning and evening peak load period form two uneven bell shapes, where demand rises before and falls after the peak load. This characteristic can be found in most of domestic load profile studies regardless of the peak load value and peak load time [7]. In general, the graphic representation of a domestic electricity load profile is mainly defined by its morning load, its evening load and its mid-day loads. The over-night load shape is defined by the low level of use in this period, as most occupants are inactive during their sleeping hours.

A study by Yohanis et al. [7] showed that, in general, as the number of occupants increases the loads during the morning and early evening periods, as defined in this work, are more pronounced when compared to consumption at mid-day. However, this characteristic does not apply to retired people or when occupants stay home for most of the day. The study also found that the average evening peak lasts 6 hours, which is longer than the morning peak average of 2 hours [7]. The relationship between the number of rooms in a household and its morning peak load has also been discussed and the derived relationship will be employed in this work. From the data presented in [8], the authors have observed that, for UK domestic household, the ratio of evening to morning peak load has a value between 1.0 and 1.8, with an average of 1.4.
In summary, the following general characteristics have been discovered based upon Y.G.Yohanis study [7].

- Evening peak load = 1.4 * Morning peak load
- Average evening peak duration (6 hours) is 4 hrs longer than morning peak duration (2 hrs)
- The relationship between number of rooms in a household and its average morning peak are show in Table 1.
- The peak load/mid-day load ratio increases with number of occupants and the number of rooms.

Table 1: Average morning peak load vs Number of rooms

Number of rooms	*1*	*2*	*3*	*4*	*5*
Average morning peak load in kW	1	1.5	4.5	5.5	6.5

2.2 Gaussian distribution for modelling hourly load profile

The Gaussian function has the following expression:

$$f_{(x)} = \text{a} \exp\left(-\frac{(\text{x}-\text{b})^2}{2\,\text{c}^2}\right) + \text{d} \qquad (1)$$

The parameter a is the height of the curve's peak, b is the position of the centre of peak, c is the width factor which controls the width of the "bell" and d is the value that the function asymptotically approaches far from the peak. For this study d is set to zero. The relationships between parameters a, b, c, d and $f_{(x)}$ are shown in Figure 2.

With respect to Gaussian distribution functions: parameter a is the peak load magnitude and, as discussed above, for each category of home it can be estimated based on the number of rooms. Parameter b is gained by averaging the times when people get up and when they leave the home. Parameter c, the curve width, is also dependent on the number of people in the home and the number of rooms.

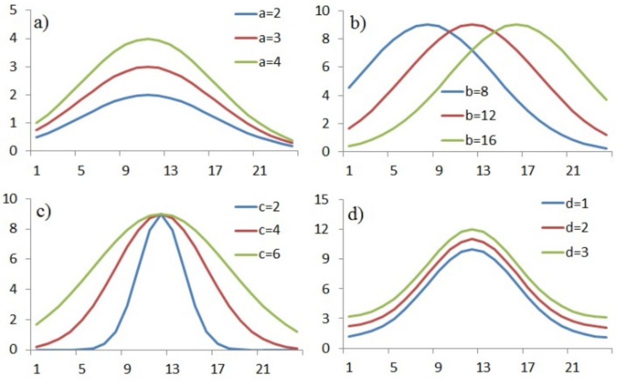

Fig 2: Gaussian function, the effect of parameters a, b, c and d on the shapes

2.3 Calculations of Gaussian Function Parameter

The main domestic load profile characteristics are contained in three time periods, morning peak period, evening peak period and mid-day period, as shown in Figure 1. The mid-night period is not included due to limited activities during the period.

Figure 3 shows an example of component functions being used to generate a household load profile shape by combining, morning peak load function (Fig. 3 a), evening peak load function (Fig. 3 b) and mid-day load function (Fig. 3 c). The mid-day load variation accounts for load consumed over the lunch period. As shown, a domestic load profile (f_{load}) can be modelled by five Gaussian distribution functions as shown in Equation (2).

$$f_{load} = f_m + f_{e1} + f_{e2} + f_{e3} + f_v \qquad (2)$$

where:

f_m is the morning peak load function shown in Fig. 3 a),

$f_e = f_{e1} + f_{e2} + f_{e3}$ are evening peak load functions considering different activity periods, Fig. 3 b),

f_v is mid-day variation load function, shown in Fig. 3 c).

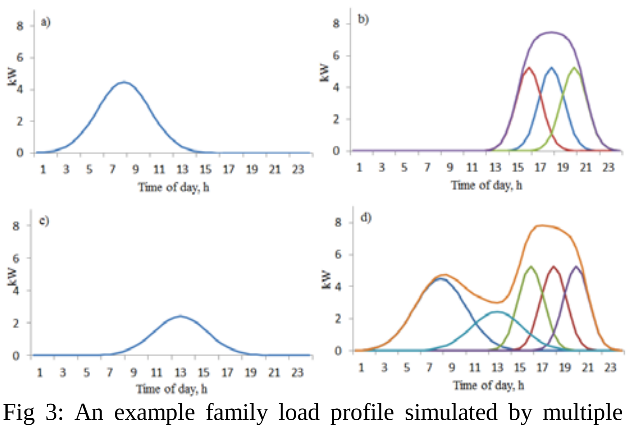

Fig 3: An example family load profile simulated by multiple Gaussian functions, a) Morning peak load function, b) Evening peak load function, c) Mid-day variation load, and d) Example family load profile

The methodology for developing the parameter applicable to each of the functions is discussed in the following sections.

2.3.1 Height parameter a

The values of the morning height parameter a_m and its corresponding Nr are showed in Table 1.

The mid-day height parameter, a_v, varies between a minimum value of 0.3 times that of a_m and its maximum value of 0.86 times a_m. The value of 0.3 is based on the occupants' behaviour using up to 30% of the domestic energy consumption [8-9]. The value of a_v decreases as the number of rooms in a household increases, as expressed in the equation below:

$$a_v = \big(0.3 + (0.7 - 0.14 * N_r)\big) * a_m \qquad (3)$$

where:

N_r is the number of rooms in a house with a maximum value of 5

0.14 is calculated as the maximum variation value $0.7a_m$ divided by maximum number of rooms 5

Based on the load profile characteristics, the parameter a_e is 1.4 times a_m. The values of a_{e1}, a_{e2} and a_{e3} are equal as shown in Fig. 3(b). The relationship between a_e and a_{e1} is shown below:

$$a_{e1} = a_{e2} = a_{e3} = \frac{a_e * \sqrt{N_p + N_r}}{\sqrt{10}} \qquad (4)$$

where:

10 is the maximum value for Np + Nr

Np is number of occupants in a household with a maximum value of 5

2.3.2 Position parameter b

The position parameter b is related to the daily activities of household occupants: t_1 is the time when the first person wakens up, t_2 is the time the last person went to work, t_3 is the time the first person gets home and t_4 is the time when the last person goes to bed. As this is a model based on Gaussian distributions, the morning peak occurs in the middle of the morning peak period and the evening peak is in the middle of evening peak period.

The values of the position parameters b have the expressions shown below:

$$b_m = (t_2 + t_1)/2 \qquad (5)$$
$$b_{e1} = (t_4 + t_3)/2 \qquad (6)$$
$$b_{e2} = b_{e1} - 2 \qquad (7)$$
$$b_{e3} = b_{e1} + 2 \qquad (8)$$
$$b_v = (t_3 + t_4)/2 \qquad (9)$$

The calculation of the values in Equation (7) and (8) represents that, on average, the evening peak period is 4 hours longer than morning peak period [9].

2.3.3 Width parameter c

The width parameter c_m is inversely proportional to the number of occupants (N_p) and the number of rooms (N_r). The width parameters need to be valued between 2 to 8 to maintain the smooth bell shape of Gaussian function in this study. The mid-day variation width parameter c_v has the same value as c_m. The three evening width parameters, c_{e1}, c_{e2} and c_{e3}, are reduced to half of c_m in order to maintain the increase/decrease rate of evening peak as show in Figure 3(b).

Following a study of suitable values for these characteristics, the following expression is developed in order to meet the conditions above.

$$c_m = c_v = 2 * c_{e1} = 2 * c_{e2} = 2 * c_{e3} = 12/\sqrt{N_p + N_r} \qquad (10)$$

3. CASE STUDIES

3.1 Five family types

The domestic electricity load profile generated by multiple Gaussian functions does not represent the exact value of electricity consumption. It is a smooth curve which approximates the hourly household electricity load profile.

Five kinds of families have been chosen in the case studies.

- Family 1: One person (None retired)
- Family 2: Married couple with no child
- Family 3: Married couple with 1-2 children
- Family 4: Married couple with 3 children
- Family 5: Lone parent depend children

According to Central Survey Unit data [10], the five family groups described above, and shown in Table 2, account for 72% of UK domestic households.

Table 2: Typical example of each family type for case study

	t1	*t2*	*t3*	*t4*	*% of total population*	*Np*	*Nr*
Family 1	8	10	17	23	15%	1	1
Family 2	7	9	16	22	24%	2	3
Family 3	6	10	16	21	17%	4	3
Family 4	5	11	15	21	6%	5	5
Family 5	7	9	16	22	10%	2	2

Figure 4 shows hourly load profiles for the five selected family groups using the proposed approach presented in the last section. The results from case studies have successfully demonstrated the following characteristics of domestic household electricity consumption.

- Peak load value increase according to number of rooms
- Peak load times appear according to the household working hours
- The peak loads are more pronounced as the number of occupants and rooms increased

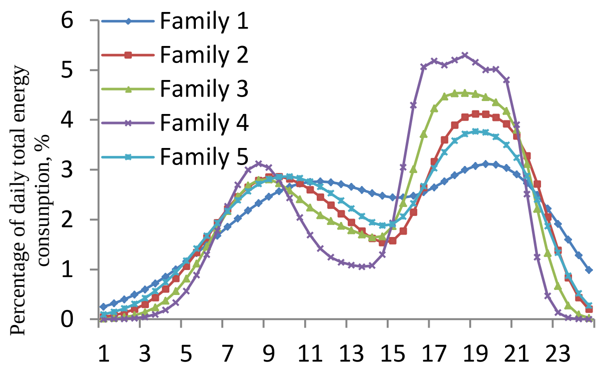

Fig 4: Electricity load profile for the five family types

3.2 Case study for regional load profile compared with National load

A region with 720 households is taken in this case study. The numbers of families in each family type are listed below in Table 3.

Table 3: Numbers of family per type for regional case study

Type	*Number in region*
Family 1	150
Family 2	240
Family 3	170
Family 4	60
Family 5	100

Outcomes are generated based on typical time and peak load variations, as per examples in Table 2. 85% of people's times of activity and occupancy varies very little, e.g. changes in ± 1 hour according to the Great British bed time report [11]. From [8, 9] the peak load difference due to human behaviour changes is ± 30%. Taking these factors into account, the modifiers applied to the case study are as follows:

$$b' = b_{e1} + n_t \qquad -1 \le n_t \le 1 \qquad (11)$$
$$b'' = b_m + n_t \qquad -1 \le n_t \le 1 \qquad (12)$$
$$a'_m = a_m * (1 + n_a) \qquad -0.3 \le n_a \le 0.3 \qquad (13)$$

n_t & n_a are generated from Gaussian normal distribution, where probability density function can be obtained by:

$$f(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2}/(2\sigma^2) \qquad (14)$$

where μ is the mean, indicating the location of maximum probability density, and σ is the standard deviation. $\sigma = 0.3$ for n_t; $\sigma = 0.1$ for n_a

Figure 5 shows the variation in load profile generated for 10 examples of typical family group 4.

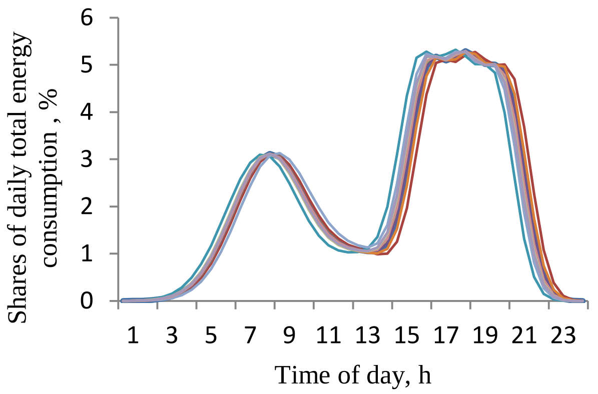

Fig 5: 10 random samples from family 4.

Figure 6 shows the normalized load from the regional grouping of 720 sampled families and the comparison with the national load research data.

The formula for the Mean Percentage Error is:

$$\mathrm{MPE} = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|m_t - a_t|}{a_t} \qquad (15)$$

where:

m_t is the modelled load result,

a_t is the measured national load [5]

n is number of time intervals. Here n=24.

The Mean Percentage Error between national load research result and the results obtained from the proposed method is 27.9%.

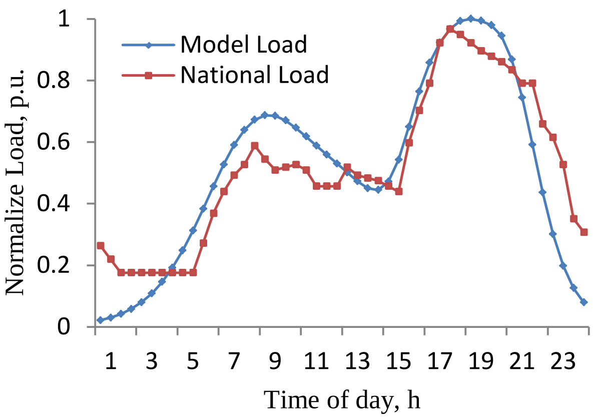

Fig 6: A comparison between the modelled results and the National load research result [5]

4. CONCLUSION AND FUTURE IMPROVEMENT

This paper introduced a practical method to generate the electricity load profile for a random household by using multiple Gaussian distribution functions. The paper comes to the following conclusions:

- Simulation results show it is possible to generate hourly domestic electricity load profile from daily electricity consumption by only six set of input data, without knowing the detailed statistical data from the household required by other published methods.
- A comparison between the simulated load profile and the measured load data from national statistics. It was found in the paper that this is a 27.9% of error due to the simplified models.
- The accuracy of this method could be improved by studying further characteristics of the electricity consumption in association with household types. The method would also benefit detailed load profile statistic data for different types of family.
- The proposed method is especially helpful to the domestic renewable energy system design, zero carbons house planning, domestic energy saving, and renewable energy policy making.

REFERENCES

[1] “Secretary of State for the Environment, Food and Rural Affairs” Climate Change the UK Programme 2006, March 2006 (3)

[2] A.Capasso, W. Grattieri, R.Lamedica,A.Prudenzi “A Bottom-up Approach to Residential Load Modelling” IEEE Transactions on Power System, Vol 9, No.2, May 1994

[3] JukkaV. Paatero, Peter D. Lund ”A Model for Generating Household Electricity Load Profiles” International Journal of Energy Research Int. J.Energy Res 2006; 30:273-290

[4] Yao, R; Steemers,K “A method of formulating energy load profile for domestic building in the UK”, Energy and Buildings Volume 37 Issue 6 (2005) 663-671

[5] Ian Richardson, Murray Thomson, David Infield “A high-resolution Domestic Building Occupancy Model for Energy Demand Simulations” Energy and Bulding 40 (2008) 1560-1566

[6] Joakim Widen, Ewa Wackelgard “A high-resolution stochastic model of domestic activity patterns and electricity demand” Applied Energy 87 (2010) 1880-1892

[7] Yigzaw G. Yohanis, Jayanta D. Mondol, Alan Wright, Brian Norton”Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use” Energy and Building 40 (2008) 1053-1059

[8] C.Palmborg, Social habits and energy consumption in single-family homes, Energy 11 (7) (1986) 643-650

[9] C. Mullaly, Home energy use behaviour: a necessary component of successful local government home energy conservation (LGHEC) program, Energy Policy 26 (14) (1998) 1041-1052.

[10] Central Survey Unit, http://www.csu.nisra.gov.uk last view on 04/08/2014

[11] The Great British bed time report, http://www.sleepcouncil.org.uk last view on 26/28/2014