View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by ResearchOnline@GCU

Glasgow Caledonian University

University for the Common Good

Domestic electricity load modelling by multiple Gaussian functions

Ge, Yan; Zhou, Chengke; Hepburn, Donald

Published in:
Energy and Buildings

DOI:
10.1016/j.enbuild.2016.05.060

Publication date:
2016

Document Version
Peer reviewed version

Link to publication in ResearchOnline

Citation for published version (Harvard):
Ge, Y, Zhou, C & Hepburn, D 2016, 'Domestic electricity load modelling by multiple Gaussian functions', *Energy and Buildings*, vol. 126, no. 8, pp. 455-462. https://doi.org/10.1016/j.enbuild.2016.05.060

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
If you believe that this document breaches copyright please view our takedown policy at https://edshare.gcu.ac.uk/id/eprint/5179 for details of how to contact us.

Download date: 29. Apr. 2020

Domestic electricity load modelling by multiple Gaussian functions

Yan Ge, Chengke Zhou, Donald M Hepburn, Glasgow Caledonian University, Glasgow, UK

Abstract:
Domestic electricity load profile is essential for energy planning and renewable energy system design. This paper presents analysis of domestic electric load characteristics and a method to model domestic and regional load profile. Multiple Gaussian functions are used to express the load characteristics in the proposed model. This is done by associating the Gaussian function parameters with the peak load changes, e.g. changing height parameters to reflect the peak magnitude. The result of the load curve represented with multiple Gaussian functions allows the model to generate a regional load profile using the number of homes, the number of bedrooms (Nr) and the number of occupants (Np). The proposed model simulates domestic load profile by its load demand change characteristics instead of its appliance ownership and use pattern, etc. Data requirement for the proposed method is significantly lower than the previous top-down and bottom-up approaches. Seasonal change is not included in the present paper, but the method is capable of including seasonal changes if each season's load demand changes in relation to Np and Nr is available. A demonstration of modelling England and Wales's national hourly load profile in 2001 and 2011 is presented in this paper. Comparison is made of the proposed method with two other published domestic load profile models. Results show that the proposed method improves the mean percentage errors by at least 5.7 % on average hourly load profile.

Key words: Electricity load modelling; Domestic load profiles; Energy-consumption; Energy planning; multiple Gaussian functions.

1. Introduction:

The growing interest in renewable energy and determination to reduce carbon emission has brought much attention to distributed generation and renewable system. Knowledge of domestic electricity load profile is essential for distributed generation system operation, renewable system design and energy planning. Domestic electricity load profile data is also required for planning low voltage networks in residential areas. The traditional domestic load modelling method often requires many input data to carry out modelling of the diversity of domestic load profile, e.g. time use of individual appliances. However such data may not be available or may be difficult to obtain at times. This paper presents a method using multiple Gaussian functions to express the load characteristics in order to reduce the data requirement for regional domestic load profile modelling.

In general, two approaches have been used in load profile modelling, Top-down and Bottom-up approaches. The Top-down approach works with macro situations and tries to attribute a load profile to its modelling target with regard of its characteristic [1], e.g. load change in relation to income level, household size, etc. The Top-down approach was also called Conditional Demand Analysis by Aigner [2] and Parti [3] in 1980s. Aigner used 24 regression equations to represent each hour in a day, five scalar variables (number of bedroom, internal temperature, etc.) and nine dummy variables (presence and absence). The energy demand of appliances is used to complete the model. The key issue with Top-down models is that they do not provide indication of variation within family and home types, resulting in a lack of detail on individual load characteristics. This is due to lack of consideration of domestic load changing characteristics in relation to scalar variables.

On the other hand the Bottom-up approaches are built up from data on a hierarchy of disaggregated components that are then combined according to estimation for their individual impact on energy usage [4]. The most commonly cited examples of the Bottom-up models are Capasso [5], Paatero [6], and Yao [7]. These models use data on ownership of appliances, individual appliance energy demands, and appliances usage time, to model the energy demand for a single household. As the authors addressed, the challenge of such modelling methods is the detailed data requirement in the range of households being considered, especially time of use of individual appliances: a complex and unpredictable human behavioural factor. Later models, e.g. Richardson [8] and Widén [9], use Time Use Survey (TUS) data to study behaviour factor in households. However, nation-wide TUS are conducted very rarely even in the developed countries, e.g. Richardson's model in year 2008 was based on year 2000 TUS report, which could result in inaccurate information being studied.

For practical regional load profile modelling, where thousands of households need to be considered at once, the model must appropriately represent each type of household accordingly. It is, however, almost impossible to obtain detailed information and usage of every single household's appliances when dealing with large numbers of homes. Some domestic load profile models attempt to overcome the issue associated with input data requirement by generating domestic load profile from similar past load profiles, based on synthesising [10] and clustering [11] techniques. Such methods may not be able to model the future load changes, since they are purely based on past load profiles. Furthermore, the synthesising and clustering methods disconnect domestic load profile from behaviour and characteristics of domestic households, e.g. occupancy time, size of households. The methods may be suitable for certain applications, but they will not provide a better understanding of domestic energy consumption behaviour. Therefore, it is important to find a method to reduce data requirement on appliance ownership and use pattern for regional domestic load profile modelling.

This paper presents an alternative view on domestic load profile modelling, where morning and evening peak load have been considered as the most important characteristics of the domestic load profile. The model uses Gaussian function's bell shape to synthesise the morning and evening peak load profile. Instead of finding each appliance's impact on peak demand, the model considers number of household occupants (Np) and number of bedrooms in the house (Nr) as the two main drives of peak demand variation. Nr represents the impact of house size on peak load demand and Np considers how the number of occupants influences the peak load demand. Three Gaussian function parameters are associated with three aspects of peak load, where height parameters (*a*) are used to synthesise peak magnitude, position parameters (*b*) are used to synthesise peak load times, and width parameters (*c*) are used to synthesise the peak duration.

The multiple Gaussian function model presented in this paper is based upon Yohanis's domestic electricity load characteristics study [12], where a household load profile was found to change with the number of persons and rooms. These factors are used to analyse domestic load characteristics.

2. Methodology and Model structure:

2.1 Domestic electricity usage characteristics

Yohanis's load characteristics study involved measurement of over 200 domestic households over a year. A sample of 27 households is selected to represent the whole population. The household types include detached, semi-detached, terraced homes and bungalow; the household size in terms of occupants includes 1 to 4+; household size in terms of bedrooms includes 2 to 5 [12]. The study found that, although the magnitude of the average daily electricity load varied, the load profiles had very similar shapes for all measured households. The minimum load occurs during the night, between 2:00 and 4:00 a.m.; a minor (morning) peak occurs between 6:00 and 9:00 a.m. and a major (evening) peak occurs between 5:00 and 10:00 p.m. These periods show consistent similarity for all studied domestic households. Although the repeat pattern of morning and evening peak load are commonly mentioned in many load profile studies, this commonality of characteristics has not been used in domestic load profile modelling.

Figure 1 shows an example of modelling of domestic load profile by combining multiple Gaussian functions. The dotted lines with markers are the five Gaussian functions used to generate an overall load profile, shown as a solid line. The modelling process will be detailed in later sections.

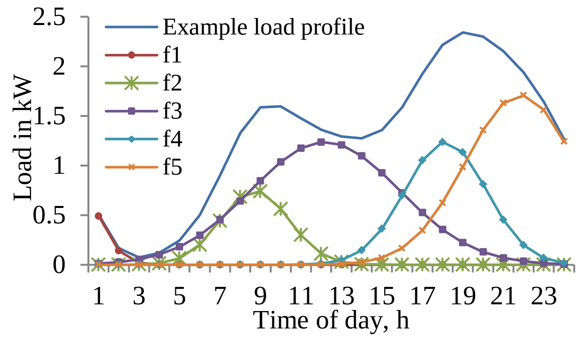

Figure 1: An example of using multiple Gaussian functions (f1-f5) to model electricity load profile.

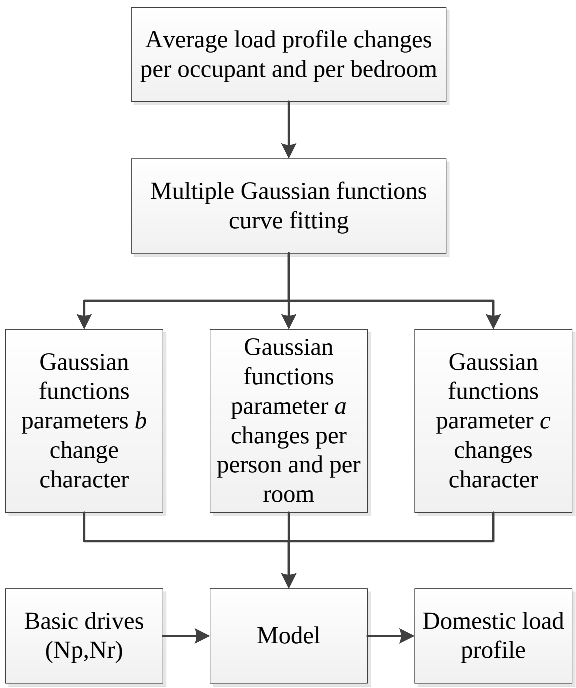

Figure 2: Flow chart of the proposed modelling process.

The flow chart of the proposed model is shown in Figure 2. The proposed model has dealt with the lack of measurement data by using Yohanis's measured load changes per occupant and per bedroom to analyse the Gaussian function parameter characteristics.

2.2 Gaussian function fitting

Figures 3 and 4, respectively, show the average domestic electricity load profile as a function of number of occupants and number of bedrooms. The data presented is calculated from Yohanis's study: average daily electricity consumption per unit floor area (m^2) as a function of number of occupants and bedrooms. The average size of standard buildings, from [13], is given in Table 1, average living space per person (44 square metres) from [14]. Sizes of households with 2 and 3 bedrooms are based on an average size of flat and house from Table 1.

Table 1: Domestic building average size in m^2

Building types	Average Size in m^2
1 Bedroom flat	46.6
2 Bedroom flat	60.7
3 Bedroom flat	86.5
1 Bedroom house	64.3
2 Bedroom house	71.2
3 Bedroom house	95.6
4 Bedroom house	120.6
5 Bedroom house	163.5

The average daily load variation per occupant and per bedroom characteristics are contained in Figures 3 and 4.

A domestic load profile can be represented by equation (1), where f_1, f_2, f_3, f_4 *and* f_5 are the Gaussian functions that build up the resultant load profile.

$$f_{load} = f_1 + f_2 + f_3 + f_4 + f_5 \qquad (1)$$

where:

$$f_n = a_n \exp\left(-\frac{(x-b_n)^2}{2\, c_n{}^2}\right)$$

$n = 1,2,3,4,5$

(a) accounts for peak load magnitude,

(b) accounts for peak load times,

(c) accounts for the peak duration

Five Gaussian functions are required in order to keep parameter accuracy within 95% of actual results. The initial time parameter values are set as 1, 6, 12, 18 and 23 to ensure that the five functions are evenly distributed over 24 hours. The initial values of magnitude and duration parameters are set at zero.

Fitting of Gaussian curve functions is performed in order to analyse those changing characteristics. The Matlab curve fitting tool box is used to produce the examples of fitting results in Figures 5 and 6.

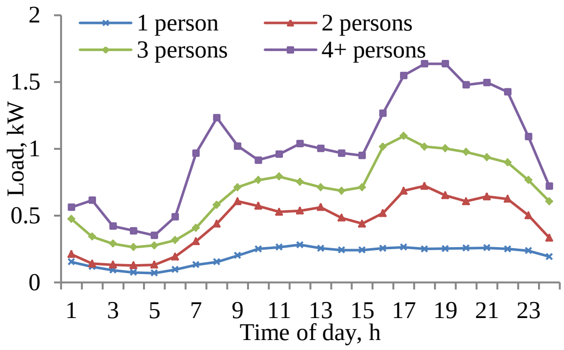

Figure 3: Average domestic electricity load profile as a function of number of occupants.

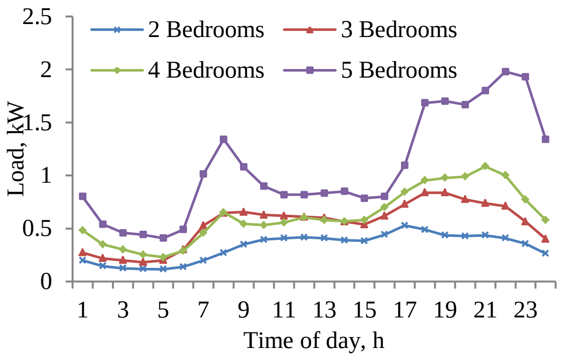

Figure 4: Average domestic electricity load profile as a function of number of bedrooms.

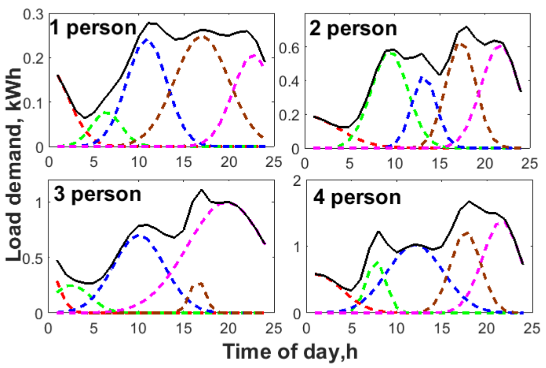

Figure 5: Curve fitting of number of persons to related load data with 95% confidence.

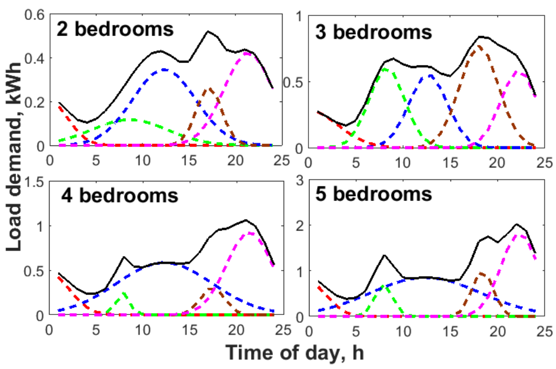

Figure 6: Curve fitting of number of bedrooms to related load data with 95% confidence.

2.3 Parameter analysis

This section presents the results of Gaussian functions fitting of 8 load profiles, shown in Figures 5 and 6.

There are 5 sets of Gaussian function parameter results from each of the 8 fitted load profiles. Each set of results contains the three Gaussian function parameters (*a*, *b and c*). The fitting of data in Figures 5 and 6 produces 120 parameter values.

In order to analyse the parameter change pattern in relation to Np and Nr, the 120 parameter results have been categorised into three groups according to type, i.e. 40 magnitude (*a*), 40 time (*b*) and 40 duration (*c*) parameters. For each group the 40 values have been categorised by Gaussian function order (n=1 to 5) and their relation to Np and Nr.

Three analysis methods are used to find the mathematical expression of the Gaussian function parameters changing pattern, namely linear relation, percentage of variations and probability density function (PDF) fitting.

2.3.1 Height parameter *a*

Figures 7 and 8 show the values of 40 height parameters in relation to Np and Nr, respectively, from Gaussian function fitting. The results show that the magnitude parameter values increase as Np and Nr increase. In general, Gaussian function parameter *a* has a linear relationship with Np and Nr.

The linear relationship between a3 and Np in Figure 7 is used as an example. Figure 9 shows the linear polynomial function result against fitting results of a3 by Np.

Repeating the process for other data in Figures 7 and 8, the magnitude parameters combined expression of Np and Nr functions are shown in equation (2), (3), (4), (5) and (6).

$$a_1 = (0.1439\ Np - 0.01695) + (0.1804\ Nr - 0.02805) \qquad (2)$$

$$a_2 = (0.1439\ Np - 0.02909) + (0.142\ Nr + 0.06415) \qquad (3)$$

$$a_3 = (0.2618\ Np - 0.0534) + (0.1545\ Nr + 0.1977) \qquad (4)$$

$$a_4 = (0.2616\,Np - 0.0457) + (0.176\,Nr + 0.1497) \tag{5}$$

$$a_5 = (0.3912\,Np - 0.1749) + (0.4553\,Nr - 0.1984) \tag{6}$$

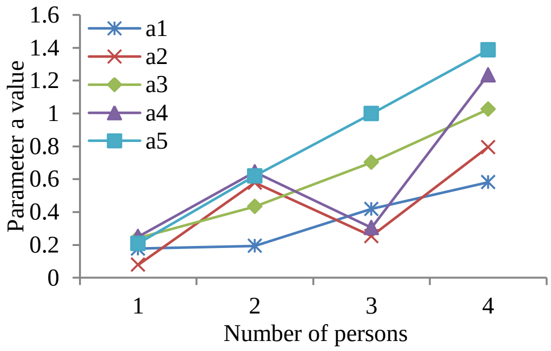

Figure 7: Magnitude parameter *a* in relation to Np

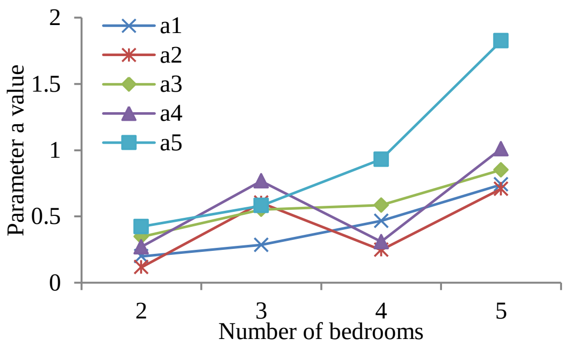

Figure 8: Magnitude parameter *a* in relation to Nr

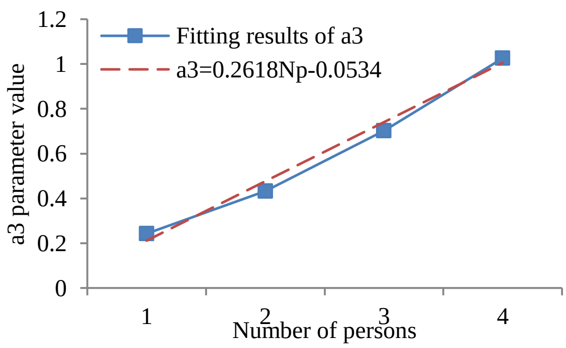

Figure 9: Magnitude parameter a_3 results by Np and linear polynomial expression.

2.3.2 Position parameter *b*

Unlike the magnitude parameter, the time parameter does not change much in relation to the number of persons and bedrooms, as shown in Figures 10 and 11. This is due to the fact that the occupancy times of average households is mainly defined by the working/school hours of the family members. The increases in the numbers of Np and Nr have very little effect on this pattern. This is because all occupants most likely have similar working/school hours.

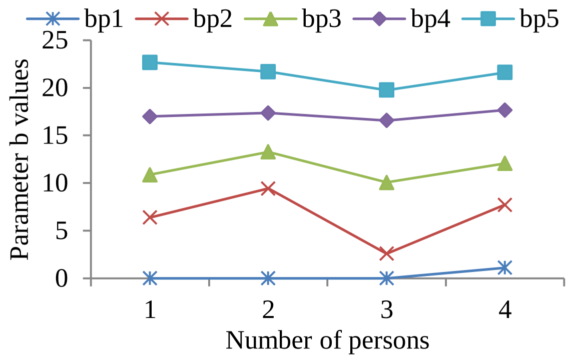

Figure 10: Time parameter *b* in relation to Np

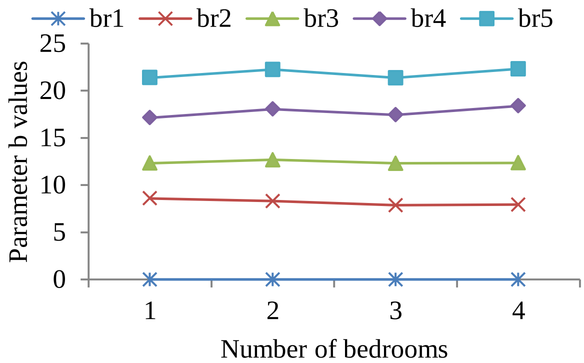

Figure 11: Time parameter *b* in relation to Nr

Therefore, the time parameter *b* can be represented as a mean value with random percentage variations, as show in equation (7). Randomising the values allows for variation in occupier's times of leaving for work, coming home, etc.

$$b_n = mean(b_n) * random\ (var(b_n)) \tag{7}$$

where:

$mean(b_n) = average(bp_n + br_n)$

$var(b_n) = mean\left(\frac{bp_n - average(bp_n)}{average(bp_n)} + \frac{br_n - average(br_n)}{average(br_n)}\right)\%$

$n = 1,2,3,4,5$

$random$: A random value is generated between 0 to $var(b_n)$

2.3.3 Duration parameter *c*

The changes in the pattern of duration parameter in relation to Np and Nr are shown in Figures 12 and 13. The duration parameters *c* do not appear to have a constant relation to Np, Nr.

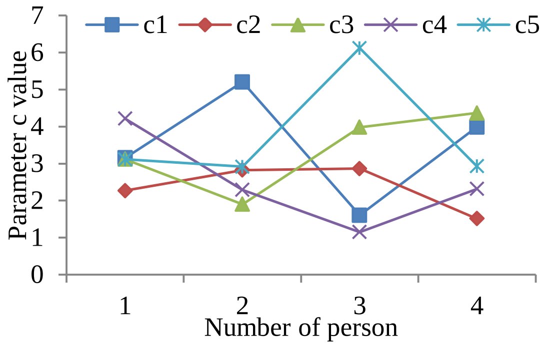

Figure 12: Duration parameter c in relation to Np

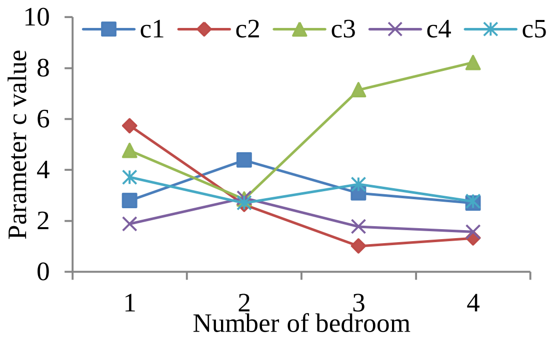

Figure 13: Duration parameter c in relation to Nr

Therefore the model assumes that the duration parameter has a random value with certain type of probability density function (PDF). The 40 width parameter *c* values shown in Figures 12 and 13 are categorised by its number of appearances in Figure 14. The PDF fitting result of 40 duration parameter values are shown in Figure 15, the lognormal PDF has the best fit with mean value (*m*) 3.24421 and variance value (*v*) 2.67782. Equation 8 is used to generate a random value of width parameter *c* for the model.

$$c_n = random\left(\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(ln\,(x)-\mu)^2}{2\sigma^2}}\right) \qquad (8)$$

where:

$$\mu = \log\left(\frac{m^2}{\sqrt{v+m^2}}\right)$$

$$\sigma = \sqrt{\log\left(\frac{v}{m^2}+1\right)}$$

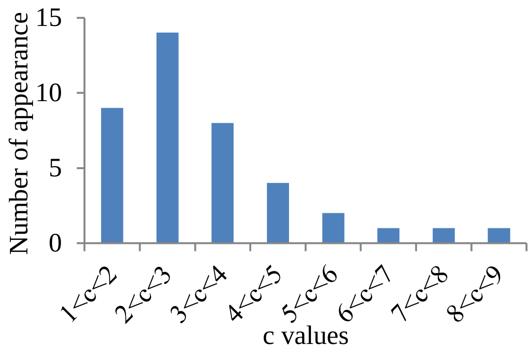

Figure 14: Number of appearances of duration parameter c

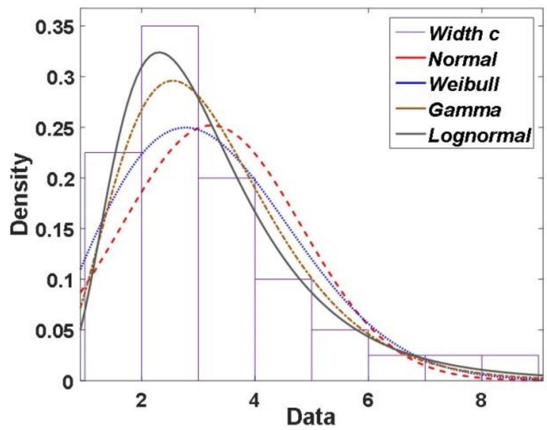

Figure 15: PDF fitting for duration parameter.

2.4 Aggregating the regional load demand

A single household load profile formula is shown in equation (9).

$$f_{(Np,Nr)} = \sum_{n=1}^{n=5}\left(\mathrm{a}_n \exp\left(-\frac{(\mathrm{x}-\mathrm{b}_n)^2}{2\,\mathrm{c}_n{}^2}\right)\right) \qquad (9)$$

A regional load equation, given by the summation of the load profiles of all households in the region, is expressed in equation (10).

$$f = \sum_{1}^{m}(N_p, N_r)\cdot f_{(Np,Nr)} \qquad (10)$$

where:

m is number of households in the region

3. Case study:

England and Wales’s national domestic electricity load profile in 2001 and 2011 have been modelled in this case study. This case only considers the impact of population changes on national domestic electricity load profile. The Office for National Statistics (ONS) reported the total number of households in England and Wales to be 21.66 million in 2001 and 23.366 million in 2011 [15, 16]. The total number of households increased by 7.87% (1.706 million) in a decade

3.1 Categorisation of family types

In order to model England and Wales's national domestic electricity load by the proposed approach, the family type data are constructed based on the 2001 and 2011 nation census data [15-18]. All the domestic households in England and Wales are categorised by number of people and bedrooms among households with consideration of the owner occupied and rented state. The number of family groups can be expressed as in equation 11.

$$M = \sum_{1}^{i=6} P_{(i)} \cdot \sum_{1}^{j=2} S_{(j)} \cdot \sum_{1}^{k=5} R_{(k)} \qquad (11)$$

where:
M is number of family groups
P is household size by number of people
S is state of a household (Owner j=1, Rented j=2)
R is household size by number of bedrooms

The number of households for each group can be calculated from the values provided in Table 2-5. Equation 12 shows an example of the calculation of the number of households which are 2 people, 3 bedrooms, owner occupied in year 2011.

$$N_{(P_{(i)},S_{(j)},R_{(k)})} = T \cdot P_{(2)} \cdot S_{(2)} \cdot R_{(3)} = 2.69 \times 10^6 \qquad (12)$$

where:
T is equal to 23.366 million (total number of households in year 2011)
$P_{(2)}$'s value is 0.36 from Table 2, 2nd row in 2011 column.
$S_{(2)}$'s value is 0.64 from Table 3, 1st row in 2011 column.
$R_{(3)}$'s value is 0.5 from Table 4, 2nd row 3rd column (the rented household should look up R's value in Table 5)

Table 2: Percentage of Household by people in England and Wales, 2001 and 2011[15, 16].

Number of people in household	2001	2011
1 person	32%	29%
2 people	34%	36%
3 people	15%	16%
4 people	13%	13%
5 people	5%	4%
6 or more people	2%	2%

Table 3: Percentage of Home Ownership and Renting [17]

House Ownership and Renting	2001	2011
Owner Occupied	69%	64%
Rented	31%	36%

Table 4: Percentage of Owner occupied households, by size and number of bedrooms in 2011 [18]

Bedroom / People	1	2	3	4	5+	SUM
1	10%	35%	45%	8%	2%	100%
2	2.5%	25%	50%	17.5%	5%	100%
3	0.5%	15%	54.5%	24%	6%	100%
4	0%	7%	53%	32%	8%	100%
5	0%	4%	41%	39%	16%	100%
6 +	0.5%	2.5%	32%	39%	26%	100%

Table 5: Percentage Rented household, by size and number of bedrooms in 2011 [18]

Bedroom / People	1	2	3	4	5+	SUM
1	51%	32%	13%	3%	1%	100%
2	20%	49%	27%	3.5%	0.5%	100%
3	6%	41%	45%	6%	2%	100%
4	2.5%	28%	55%	12%	2.5%	100%
5	2%	16%	57%	17%	8%	100%
6 +	2%	9%	48%	24%	17%	100%

For the case study, as the 2001 census report did not provide information related to the size and number of bedrooms, the percentage in each classification for 2001 is assumed to be the same as that in 2011.

3.2 Results and validation

3.2.1 Examples of individual family household load profile

Ten load profile examples are shown in Figures 16 and 17. Figure 16 includes five examples of electricity load of one person living in one bedroom. Figure 17 shows results of five load profiles of three persons living in two bedroom accommodation. Each example is different because of the random values used for Gaussian function parameters *b* and *c*. But all ten results show common characteristics of domestic load profile which have two peak periods (morning and evening) and variations before or after peak.

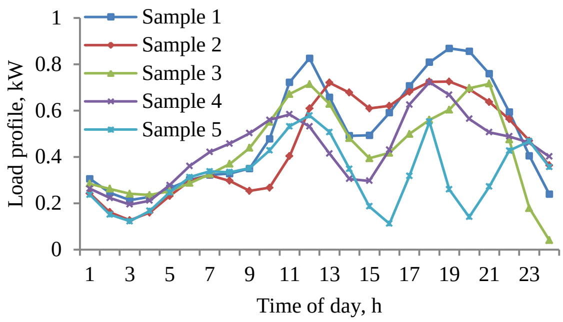

Figure 16: 5 Load demand profiles for 1 person in 1 bedroom accommodation

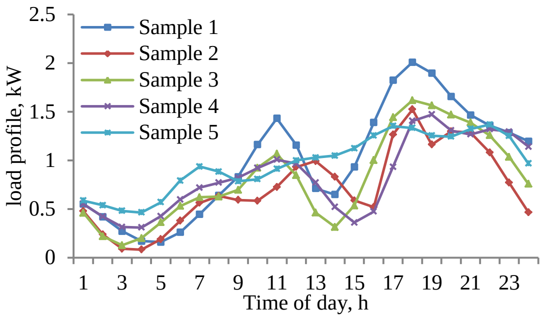

Figure 17: 5 Load demand profile of 3 persons in 2 bedroom accommodation

Comparison between Figures 16 and 17 shows the peak loads have increased, as expected, with changes in Np and Nr. Figures 16 and 17 share similar load characteristics to measurement results in Figures 3 and 4, e.g. low activity level in early morning and late evening, increase in electricity demand during the two peak periods, etc.

3.2.2 England and Wales national load model results for Year 2001 and 2011

Modelling results of hourly domestic electricity use in England and Wales in 2001 and 2011 are presented in Figure 18. The model results for both years have a very similar shape. The 2011 average load magnitude increased smoothly between 7 a.m. and 10 p.m. The mid-night time has not changed much, this is because the population increase would not change the fact people do not consume much electrical power during mid-night hours.

This similar load changing character can also be found in the England and Wales's national electricity load (includes domestic, commercial and industry) in Figure 19, where the overall electricity consumption behaviour did not change much over the years. The mid-night load increase in Figure 19 is because many commercial and industrial energy users still consumed electricity during the mid-night time. Figure 19 also shows a decrease of electricity load demand from 2006 to 2011. The model, as shown in Figure 18, failed to represent this decrease in electricity load demand. This is because there is only one year's data on load demand in relation to the number of occupant (Np) and bedrooms (Nr) data used for load characteristics analysis. This could be improved when multiple years' average load becomes available for load characteristics analysis.

The modelling results suggest that the population and number of households have very little impact on national domestic electricity load profiles in terms of load shapes over the ten year period investigated. Comparison of the modelling and real data indicates that energy efficiency and other measures have a much greater impact on energy demand than population changes.

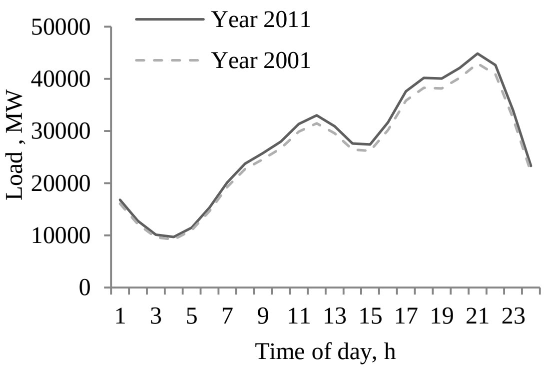

Figure 18: Modelling result of 2001 and 2011 England and Wales's electricity load.

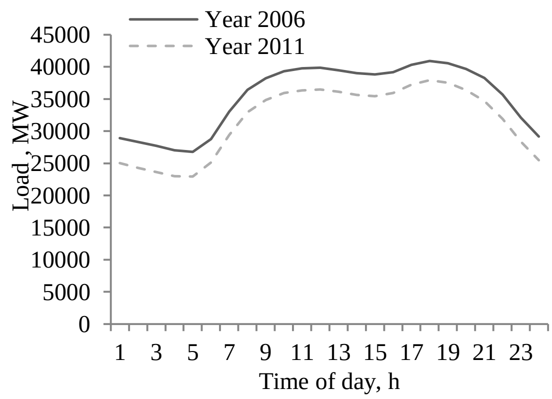

Figure 19: England and Wales's national electricity load 2006 and 2011 [19].

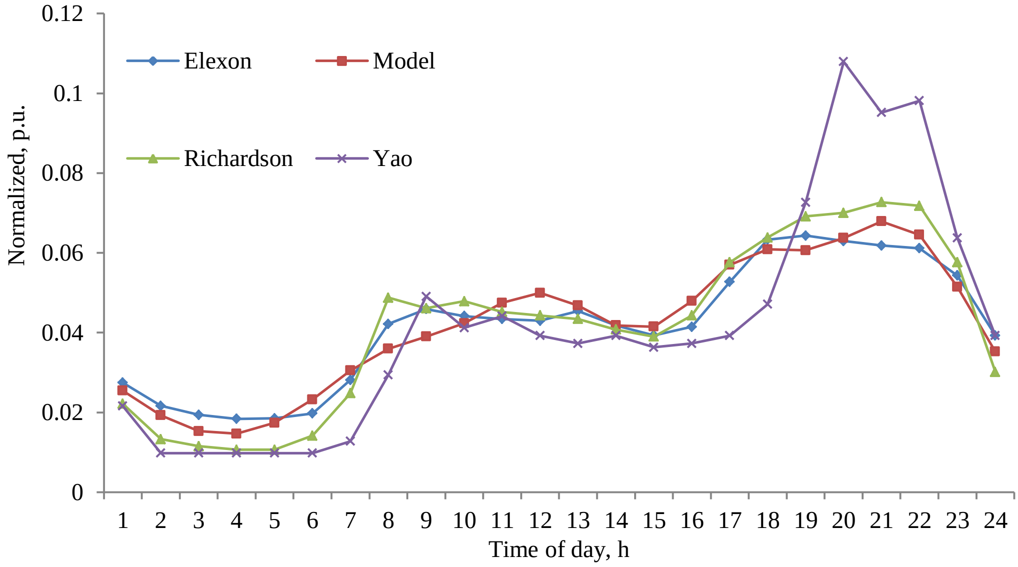

Figure 20: Result from present model, Yao model, Richardson model, and reference load from Elexon.

3.2.3 Result comparison with past models

A comparison of mean percentage errors (MPE) between the proposed model and two other published models (Yao [7] and Richardson [8]) and measured data Elexon published [20] on average domestic load profile are shown in Figure 20. The MPE formula used in this comparison is shown in equation 13.

$$\mathrm{MPE} = \frac{100\%}{n}\sum_{t=1}^{n}\frac{|m_t - a_t|}{a_t} \qquad (13)$$

where:
m_t is the modelled load result,
a_t is the comparison target result,
n is number of time intervals. Here n=24.

The result shows that the model presented in this paper has the lowest MPE 9.4% in comparison with Richardon's 15.1% and Yao's 28.6%. This shows a 5.7% improvement over the past models. The proposed model has the closest match on evening peak load demand and on early morning load, between 1AM and 6 AM. The proposed method did not have the best result on morning peak load, as it has a later morning peak time than others. The cause of this will be discussed in the next section.

In addition to having greater overall accuracy, the proposed model also uses less input data. Firstly, both Yao and Richardson's models required data on appliances ownership, whereas the proposed model does not need to know any details on appliances. Secondly, Richardson's model used TUS data as input, which is much more complex than Yohanis's 27 household electrical load measurements.

The model proposed in this paper made it possible to model national domestic electricity load profile characteristics from a small number of measurement results combined with the national census data. The simplicity of this method makes it possible to apply it to situations where there is a lack of domestic load profile statistical data.

3.2.4 Characteristics, reference and model result data comparisons

In order to explain why the model did not produce a better result during morning peak period, a comparison between total average load of Yohanis's characteristic study, Elexon reference load and the model's result is shown in Figure 21.

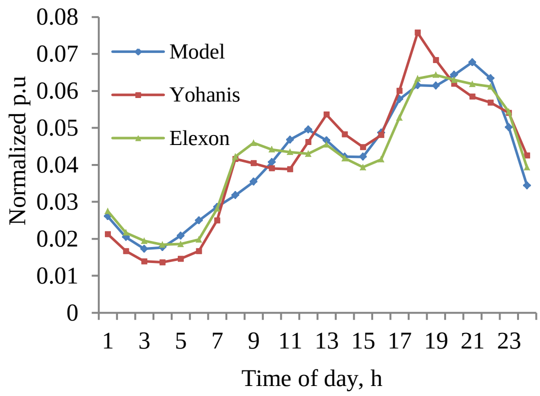

Figure 21: Yohanis study's average load profile in comparison to model result and Elexon's reference load.

This shows the Yohanis average domestic load profile has a much later morning peak time compared with the reference load. The position parameter *b* analysis process picked up this late morning peak time characteristics from Yohanis's data. This could be caused by the fact that Yohanis study only measured 27 households, where the small number of individual families had too much impact on average load profile. On the other hand, it also demonstrated that the proposed method is very effective in capturing the characteristic information from the measured data.

4. Conclusions and Discussions:

This paper introduced a novel method for determining regional electrical load through a minimum amount of information. The application of a multiple Gaussian function based method to model domestic household electricity load profile using the number of households in a region. Input data uses readily available information, or that which could be estimated for a proposed housing development, i.e. the number of persons Np and bedrooms and Nr of the households. The presented model is based on Yohanis's domestic load profile characteristic study. Other domestic load studies based on measurement result with load changes per occupant and per bedroom can also serve the same purpose. Gaussian function curve fitting are used to analyse the load characteristic variation with Np, Nr.

This paper provided insights to the characteristics using mathematical expressions which are then integrated into a load profile model to generate synthetic data. The model is capable of generating a regional load profile with different household composition and population, assuming the analysis target have similar load characteristics. The method can also effectively represent the national electricity characteristics from measurement results of small number of household (27 household).

The model could be improved in two of the following areas:

I) Improve domestic load profile characteristic study: i) The method will benefit from more detailed characteristic study, e.g. mid-day load change characteristics per occupant and per bedroom. ii) Increasing the number of households measured in the characteristic study will also improve the model accuracy, e.g. the late morning peak in Yohanis's study leads to errors in the modelling result. iii) Better categorisation of the measured households could improve the model result, e.g. Yohanis's study only provided average load profile changes per occupants and bedrooms, by providing different type of household load profile changes per occupant and bedroom would improve the variety and accuracy of the model result. iv) Seasonal load profile change can be included in the model if each season's load change per occupant and per bedroom is provided in load characteristics study.

II) Further Gaussian parameters analysis: some Gaussian parameter relations to the Np and Nr require further investigation. i) The magnitude parameter values (a2, a4) drop at 3 person and 4 bedrooms, shown in Figures 6 and 7. ii) The unusual duration parameter changes with three bedroom households in Figure 11. These indicate that certain types of family may require additional analysis. Increasing the number of data points for duration parameter will give a more complete picture of duration parameter characteristics and better analysis result.

Reference:

[1] A.Grandjean, J.Adnot, G.Binet, A review and analysis of the residential electric load curve models, Renewable and Sustainable Energy Review 16 (2012) 6539-6565

[2] D.Aigner, C.Sorooshian, P.Kerwin, Conditional demand analysis for estimating residential end-use load profiles. The Energy Journal 1984; 5(3):81-97

[3] M.Parti, C.Parti, The total and appliance-specific conditional demand for electricity in the household sector. Bell Journal of Economic 1980;11(1):309-21

[4] M.Kavgic, A.Mavrogianni, D.Mumovic, A.Summerfield, et al, A review of bottom-up building stock models for energy consumption in the residential sector; Building and Enviorments 45 (2010) 1683-1697

[5] A. Capasso, W. Grattieri, R. Lamedica, and A. Prudenzi, Bottom-up approach to residential load modeling, IEEE Trans. Power Syst., vol. 9, pp. 957–964, 1994.

[6] J. V. Paatero and P. D. Lund, A model for generating household electricity load profiles, Int. J. Energy Res., vol. 30, pp. 273–290, 2006.

[7] R. Yao and K. Steemers, A method of formulating energy load profile for domestic buildings in the UK, Energy Build., vol. 37, pp. 663–671, 2005.

[8] I. Richardson, M. Thomson, D. Infield, and C. Clifford, Domestic electricity use: A high-resolution energy demand model, Energy Build., vol. 42, pp. 1878–1887, 2010.

[9] J. Widén and E. Wäckelgård, A high-resolution stochastic model of domestic activity patterns and electricity demand, Appl. Energy, vol. 87, pp. 1880–1892, 2010.

[10] D.P.Jenkins, S.Patidar, S.A.Simpson, Synthesising electrical demand profiles for UK dwellings. Energy and Buildings76 (2014) 605-614, doi:10.1016/j.enbuild.2014.03.012

[11] F. Mcloughlin, A.Duffy, M.Conlon, A clustering approach to domestic electricity load profile characterisation using smar metering data, Apply energy 141 (2015) 190-199 doi:10.1016/j.apenergy.2014.12.039

[12] Y. G. Yohanis, J. D. Mondol, A. Wright, and B. Norton, Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use, Energy Build., vol. 40, pp. 1053–1059, 2008.

[13] Housing standards: evidence and research dwelling size survey. A report prepared by Scott Wilson for CABE, April 2010.

[14] K. Williams, Space per person in the UK: A review of densities, trends, experiences and optimum levels, Land Use Policy 26S (2009)S83-S92

[15] Office for National Statistics, English Housing Survey: Households 2010-11. Office National Statistics, July 2012

[16] Office for National Statistics, Living in Britain: Result from the 2000/01 General Household Survey, 2001

[17] Office for National Statistics, A Century of Home Ownership and Renting in England and Wales (Full story), Part of 2011 Census Analysis, 19th April 2013

[18] Office for National Statistic, Home ownership and renting in England and Wales- Detailed Characteristics, Part of 2011 Census, Detailed characteristics on Housing for Local Authorities in England and Wales Release 28th June 2013

[19] NationalGrid, DemandData_historic 2006 and 2011, http://www2.nationalgrid.com/UK/Industry-information/Electricity-transmission-operational-data/Data-Explorer/ last review in 06th December 2015

[20] ELEXON, Load profiles and their use in Electricity Settlement version 2.0, 7th November 2013.