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# Domestic electricity load modelling by multiple Gaussian functions

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## **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 ( $N_r$ ) and the number of occupants ( $N_p$ ). 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  $N_p$  and  $N_r$  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

78 demand for a single household. As the authors  
79 addressed, the challenge of such modelling  
80 methods is the detailed data requirement in the  
81 range of households being considered, especially  
82 time of use of individual appliances: a complex and  
83 unpredictable human behavioural factor. Later  
84 models, e.g. Richardson [8] and Widén [9], use  
85 Time Use Survey (TUS) data to study behaviour  
86 factor in households. However, nation-wide TUS  
87 are conducted very rarely even in the developed  
88 countries, e.g. Richardson's model in year 2008  
89 was based on year 2000 TUS report, which could  
90 result in inaccurate information being studied.

91  
92 For practical regional load profile modelling, where  
93 thousands of households need to be considered at  
94 once, the model must appropriately represent each  
95 type of household accordingly. It is, however,  
96 almost impossible to obtain detailed information  
97 and usage of every single household's appliances  
98 when dealing with large numbers of homes. Some  
99 domestic load profile models attempt to overcome  
100 the issue associated with input data requirement by  
101 generating domestic load profile from similar past  
102 load profiles, based on synthesising [10] and  
103 clustering [11] techniques. Such methods may not  
104 be able to model the future load changes, since they  
105 are purely based on past load profiles. Furthermore,  
106 the synthesising and clustering methods disconnect  
107 domestic load profile from behaviour and  
108 characteristics of domestic households, e.g.  
109 occupancy time, size of households. The methods  
110 may be suitable for certain applications, but they  
111 will not provide a better understanding of domestic  
112 energy consumption behaviour. Therefore, it is  
113 important to find a method to reduce data  
114 requirement on appliance ownership and use  
115 pattern for regional domestic load profile modelling.

116  
117 This paper presents an alternative view on domestic  
118 load profile modelling, where morning and evening  
119 peak load have been considered as the most  
120 important characteristics of the domestic load  
121 profile. The model uses Gaussian function's bell  
122 shape to synthesise the morning and evening peak  
123 load profile. Instead of finding each appliance's  
124 impact on peak demand, the model considers  
125 number of household occupants ( $N_p$ ) and number  
126 of bedrooms in the house ( $N_r$ ) as the two main  
127 drivers of peak demand variation.  $N_r$  represents the  
128 impact of house size on peak load demand and  $N_p$   
129 considers how the number of occupants influences

130 the peak load demand. Three Gaussian function  
131 parameters are associated with three aspects of  
132 peak load, where height parameters ( $a$ ) are used to  
133 synthesise peak magnitude, position parameters ( $b$ )  
134 are used to synthesise peak load times, and width  
135 parameters ( $c$ ) are used to synthesise the peak  
136 duration.

137  
138 The multiple Gaussian function model presented in  
139 this paper is based upon Yohanis's domestic  
140 electricity load characteristics study [12], where a  
141 household load profile was found to change with  
142 the number of persons and rooms. These factors are  
143 used to analyse domestic load characteristics.

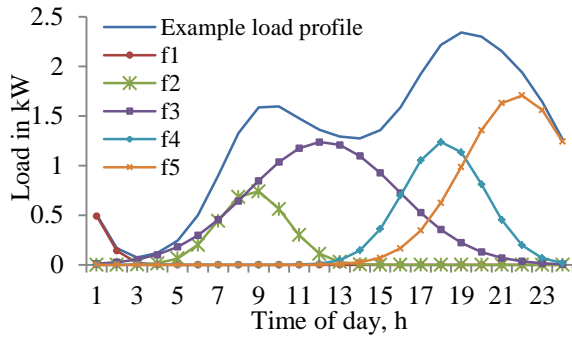
## 144 145 **2. Methodology and Model structure:**

### 146 147 **2.1 Domestic electricity usage characteristics**

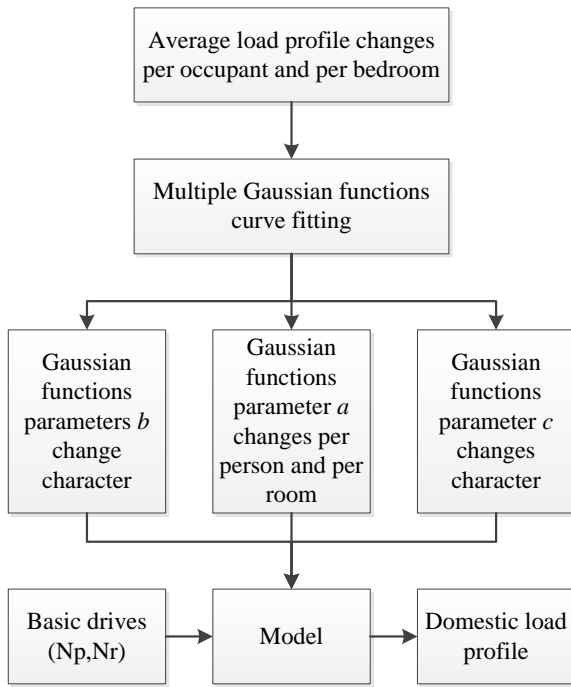
148  
149 Yohanis's load characteristics study involved  
150 measurement of over 200 domestic households  
151 over a year. A sample of 27 households is selected  
152 to represent the whole population. The household  
153 types include detached, semi-detached, terraced  
154 homes and bungalow; the household size in terms  
155 of occupants includes 1 to 4+; household size in  
156 terms of bedrooms includes 2 to 5 [12]. The study  
157 found that, although the magnitude of the average  
158 daily electricity load varied, the load profiles had  
159 very similar shapes for all measured households.  
160 The minimum load occurs during the night,  
161 between 2:00 and 4:00 a.m.; a minor (morning)  
162 peak occurs between 6:00 and 9:00 a.m. and a  
163 major (evening) peak occurs between 5:00 and  
164 10:00 p.m. These periods show consistent  
165 similarity for all studied domestic households.  
166 Although the repeat pattern of morning and  
167 evening peak load are commonly mentioned in  
168 many load profile studies, this commonality of  
169 characteristics has not been used in domestic load  
170 profile modelling.

171  
172 Figure 1 shows an example of modelling of  
173 domestic load profile by combining multiple  
174 Gaussian functions. The dotted lines with markers  
175 are the five Gaussian functions used to generate an  
176 overall load profile, shown as a solid line. The  
177 modelling process will be detailed in later sections.

178



179  
180 Figure 1: An example of using multiple Gaussian  
181 functions (f1-f5) to model electricity load profile.  
182



183  
184  
185 Figure 2: Flow chart of the proposed modelling  
186 process.  
187

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

## 195 2.2 Gaussian function fitting

196  
197 Figures 3 and 4, respectively, show the average  
198 domestic electricity load profile as a function of  
199 number of occupants and number of bedrooms. The  
200 data presented is calculated from Yohanis's study:  
201 average daily electricity consumption per unit floor  
202 area ( $m^2$ ) as a function of number of occupants and  
203 bedrooms. The average size of standard buildings,

204 from [13], is given in Table 1, average living space  
205 per person (44 square metres) from [14]. Sizes of  
206 households with 2 and 3 bedrooms are based on an  
207 average size of flat and house from Table 1.

208 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

210  
211 The average daily load variation per occupant and  
212 per bedroom characteristics are contained in  
213 Figures 3 and 4.

214  
215 A domestic load profile can be represented by  
216 equation (1), where  $f_1, f_2, f_3, f_4$  and  $f_5$  are the  
217 Gaussian functions that build up the resultant load  
218 profile.

$$220 f_{load} = f_1 + f_2 + f_3 + f_4 + f_5 \quad (1)$$

221 where:

$$223 f_n = a_n \exp\left(-\frac{(x-b_n)^2}{2c_n^2}\right)$$

$$224 n = 1,2,3,4,5$$

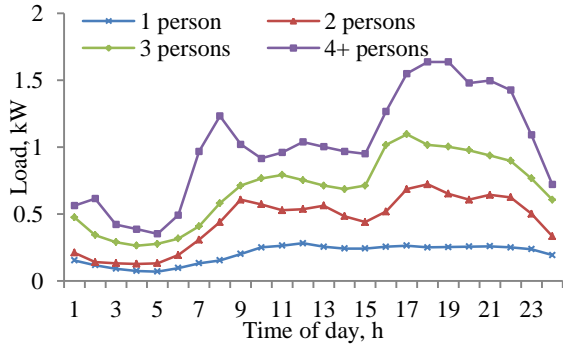
225 (a) accounts for peak load magnitude,

226 (b) accounts for peak load times,

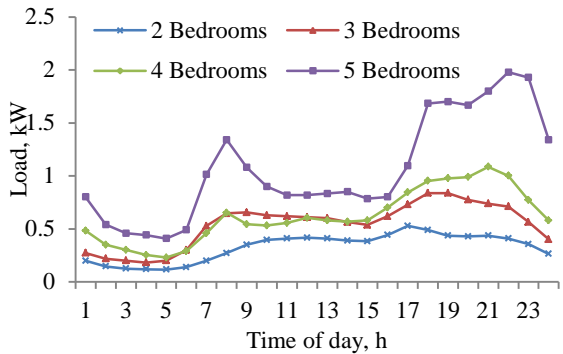
227 (c) accounts for the peak duration

228 Five Gaussian functions are required in order to  
229 keep parameter accuracy within 95% of actual  
230 results. The initial time parameter values are set as  
231 1, 6, 12, 18 and 23 to ensure that the five functions  
232 are evenly distributed over 24 hours. The initial  
233 values of magnitude and duration parameters are  
234 set at zero.

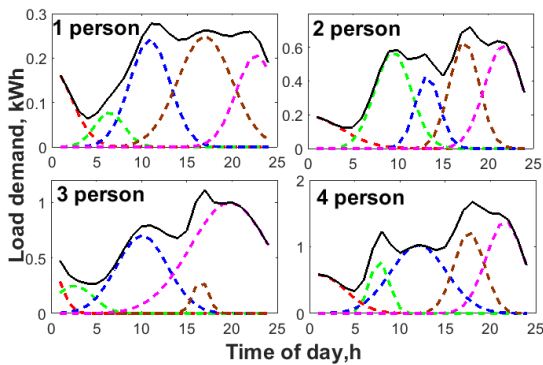
235  
236 Fitting of Gaussian curve functions is performed in  
237 order to analyse those changing characteristics. The  
238 Matlab curve fitting tool box is used to produce the  
239 examples of fitting results in Figures 5 and 6.



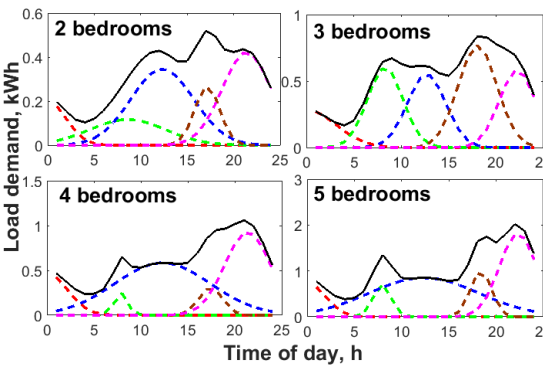
240  
241 Figure 3: Average domestic electricity load profile  
242 as a function of number of occupants.  
243



244  
245 Figure 4: Average domestic electricity load profile  
246 as a function of number of bedrooms.  
247



248  
249 Figure 5: Curve fitting of number of persons to  
250 related load data with 95% confidence.  
251



252  
253 Figure 6: Curve fitting of number of bedrooms to  
254 related load data with 95% confidence.  
255  
256

## 57 2.3 Parameter analysis

58  
59 This section presents the results of Gaussian  
60 functions fitting of 8 load profiles, shown in  
61 Figures 5 and 6.

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

267 In order to analyse the parameter change pattern in  
268 relation to *N<sub>p</sub>* and *N<sub>r</sub>*, the 120 parameter results  
269 have been categorised into three groups according  
270 to type, i.e. 40 magnitude (*a*), 40 time (*b*) and 40  
271 duration (*c*) parameters. For each group the 40  
272 values have been categorised by Gaussian function  
273 order (*n*=1 to 5) and their relation to *N<sub>p</sub>* and *N<sub>r</sub>*.

274  
275 Three analysis methods are used to find the  
276 mathematical expression of the Gaussian function  
277 parameters changing pattern, namely linear relation,  
278 percentage of variations and probability density  
279 function (PDF) fitting.

280

### 281 2.3.1 Height parameter *a*

282

283 Figures 7 and 8 show the values of 40 height  
284 parameters in relation to *N<sub>p</sub>* and *N<sub>r</sub>*, respectively,  
285 from Gaussian function fitting. The results show  
286 that the magnitude parameter values increase as *N<sub>p</sub>*  
287 and *N<sub>r</sub>* increase. In general, Gaussian function  
288 parameter *a* has a linear relationship with *N<sub>p</sub>* and  
289 *N<sub>r</sub>*.

290

291 The linear relationship between *a<sub>3</sub>* and *N<sub>p</sub>* in  
292 Figure 7 is used as an example. Figure 9 shows the  
293 linear polynomial function result against fitting  
294 results of *a<sub>3</sub>* by *N<sub>p</sub>*.

295

296 Repeating the process for other data in Figures 7  
297 and 8, the magnitude parameters combined  
298 expression of *N<sub>p</sub>* and *N<sub>r</sub>* functions are shown in  
299 equation (2), (3), (4), (5) and (6).

300

$$301 a_1 = (0.1439 N_p - 0.01695) + (0.1804 N_r -$$

$$302 0.02805) \quad (2)$$

$$303 a_2 = (0.1439 N_p - 0.02909) + (0.142 N_r +$$

$$304 0.06415) \quad (3)$$

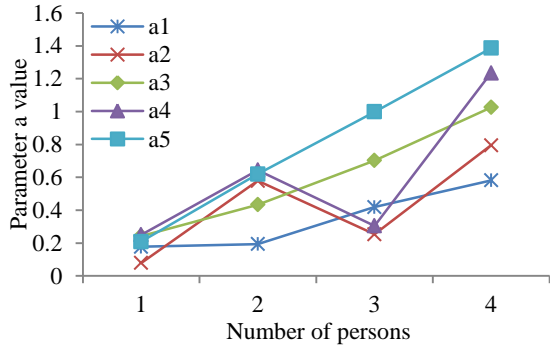
$$305 a_3 = (0.2618 N_p - 0.0534) + (0.1545 N_r +$$

$$306 0.1977) \quad (4)$$

307  $a_4 = (0.2616 Np - 0.0457) + (0.176 Nr +$   
 308  $0.1497)$  (5)

309  $a_5 = (0.3912 Np - 0.1749) + (0.4553 Nr -$   
 310  $0.1984)$  (6)

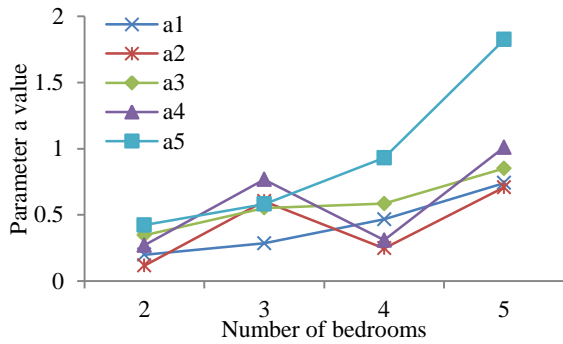
311



312

313 Figure 7: Magnitude parameter  $a$  in relation to  $Np$

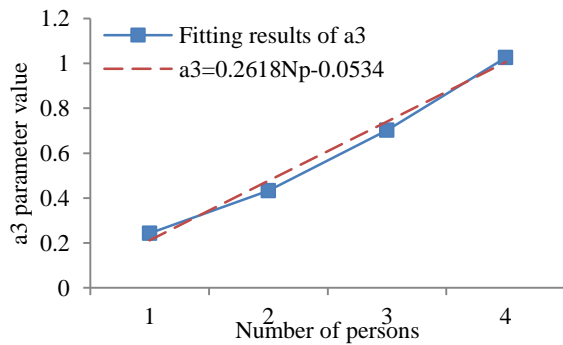
314



315

316 Figure 8: Magnitude parameter  $a$  in relation to  $Nr$

317



318

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

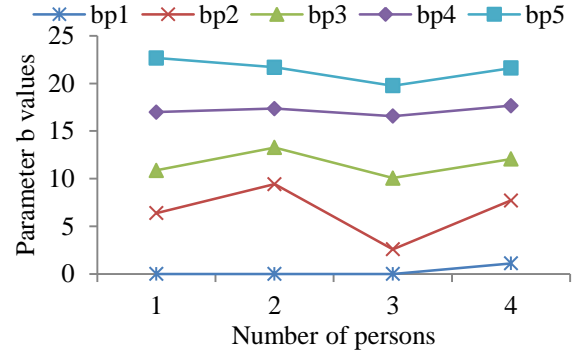
### 321 2.3.2 Position parameter $b$

322

323 Unlike the magnitude parameter, the time  
 324 parameter does not change much in relation to the  
 325 number of persons and bedrooms, as shown in  
 326 Figures 10 and 11. This is due to the fact that the  
 327 occupancy times of average households is mainly

328 defined by the working/school hours of the family  
 329 members. The increases in the numbers of  $Np$  and  
 330  $Nr$  have very little effect on this pattern. This is  
 331 because all occupants most likely have similar  
 332 working/school hours.

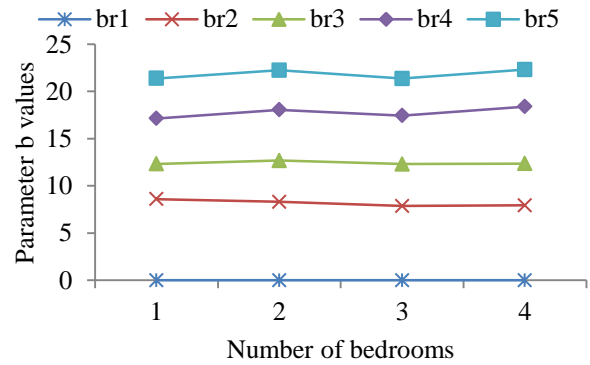
333



334

335 Figure 10: Time parameter  $b$  in relation to  $Np$

336



337

338 Figure 11: Time parameter  $b$  in relation to  $Nr$

339

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

345

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

347

348 where:

349  $\text{mean}(b_n) = \text{average}(bp_n + br_n)$

350  $\text{var}(b_n) = \text{mean}(\frac{bp_n - \text{average}(bp_n)}{\text{average}(bp_n)} +$

$\frac{br_n - \text{average}(br_n)}{\text{average}(br_n)}) \%$

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

351  $\text{random}$ : A random value is generated between 0

352 to  $\text{var}(b_n)$

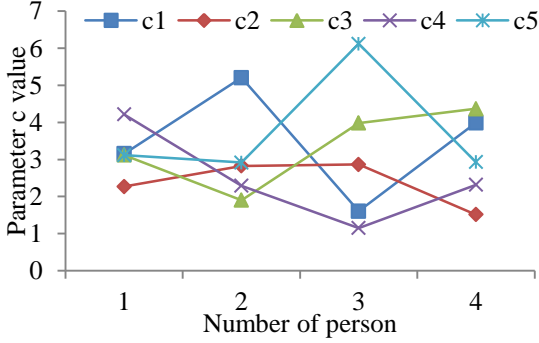
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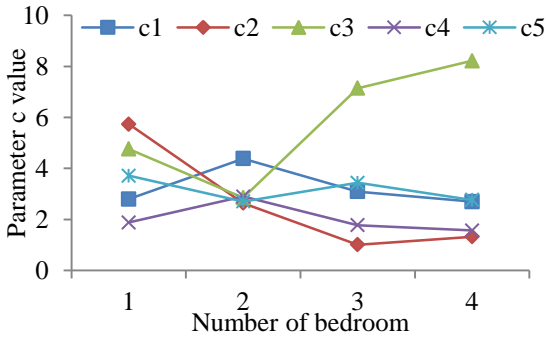
355

### 356 2.3.3 Duration parameter $c$

357 The changes in the pattern of duration parameter in  
 358 relation to  $N_p$  and  $N_r$  are shown in Figures 12 and  
 359 13. The duration parameters  $c$  do not appear to  
 360 have a constant relation to  $N_p$ ,  $N_r$ .  
 361



362  
 363 Figure 12: Duration parameter  $c$  in relation to  $N_p$   
 364



365  
 366 Figure 13: Duration parameter  $c$  in relation to  $N_r$   
 367

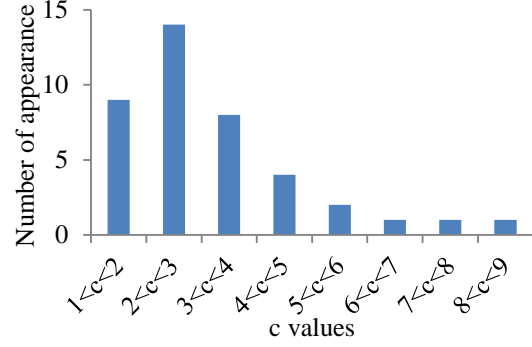
368 Therefore the model assumes that the duration  
 369 parameter has a random value with certain type of  
 370 probability density function (PDF). The 40 width  
 371 parameter  $c$  values shown in Figures 12 and 13 are  
 372 categorised by its number of appearances in Figure  
 373 14. The PDF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

$$379 \quad c_n = \text{random} \left( \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}} \right) \quad (8)$$

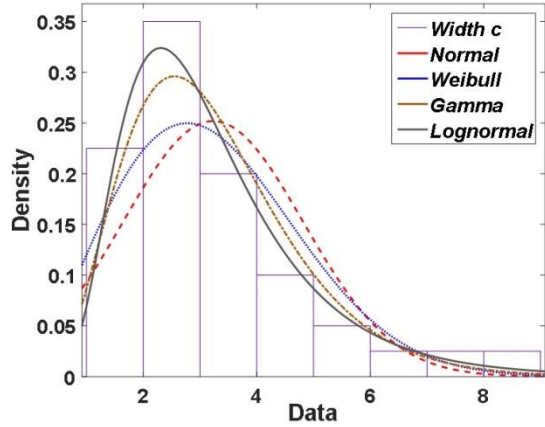
380 where:

$$381 \quad \mu = \log\left(\frac{m^2}{\sqrt{v+m^2}}\right)$$

$$382 \quad \sigma = \sqrt{\log\left(\frac{v}{m^2} + 1\right)}$$



383  
 384 Figure 14: Number of appearances of duration  
 385 parameter  $c$   
 386



387  
 388 Figure 15: PDF fitting for duration parameter.  
 389

#### 390 2.4 Aggregating the regional load demand

391  
 392 A single household load profile formula is shown  
 393 in equation (9).

$$394 \quad f_{(N_p, N_r)} = \sum_{n=1}^{n=5} \left( a_n \exp\left(-\frac{(x-b_n)^2}{2c_n^2}\right) \right) \quad (9)$$

395  
 396 A regional load equation, given by the summation  
 397 of the load profiles of all households in the region,  
 398 is expressed in equation (10).  
 399

$$400 \quad f = \sum_1^m (N_p, N_r) \cdot f_{(N_p, N_r)} \quad (10)$$

401

402 where:

403  $m$  is number of households in the region

404

#### 405 3. Case study:

406

407 England and Wales's national domestic electricity  
 408 load profile in 2001 and 2011 have been modelled  
 in this case study. This case only considers the

409 impact of population changes on national domestic  
 410 electricity load profile. The Office for National  
 411 Statistics (ONS) reported the total number of  
 412 households in England and Wales to be 21.66  
 413 million in 2001 and 23.366 million in 2011 [15, 16].  
 414 The total number of households increased by 7.87%  
 415 (1.706 million) in a decade  
 416

### 417 3.1 Categorisation of family types

418  
 419 In order to model England and Wales's national  
 420 domestic electricity load by the proposed approach,  
 421 the family type data are constructed based on the  
 422 2001 and 2011 nation census data [15-18]. All the  
 423 domestic households in England and Wales are  
 424 categorised by number of people and bedrooms  
 425 among households with consideration of the owner  
 426 occupied and rented state. The number of family  
 427 groups can be expressed as in equation 11.  
 428

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

429

430 where:

431  $M$  is number of family groups

432  $P$  is household size by number of people

433  $S$  is state of a household (Owner  $j=1$ , Rented  $j=2$ )

434  $R$  is household size by number of bedrooms  
 435

436 The number of households for each group can be  
 437 calculated from the values provided in Table 2-5.  
 438 Equation 12 shows an example of the calculation of  
 439 the number of households which are 2 people, 3  
 440 bedrooms, owner occupied in year 2011.  
 441

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

442

443 where:

444  $T$  is equal to 23.366 million (total number of  
 445 households in year 2011)

446  $P_{(2)}$ 's value is 0.36 from Table 2, 2<sup>nd</sup> row in 2011  
 447 column.

448  $S_{(2)}$ 's value is 0.64 from Table 3, 1<sup>st</sup> row in 2011  
 449 column.

450  $R_{(3)}$ 's value is 0.5 from Table 4, 2<sup>nd</sup> row 3<sup>rd</sup> column  
 451 (the rented household should look up  $R$ 's value in  
 452 Table 5)  
 453  
 454  
 455  
 456

457 Table 2: Percentage of Household by people in  
 458 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%

459

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

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

462

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

Bedroom	1	2	3	4	5+	SUM
<b>People</b>						
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%

465

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

Bedroom	1	2	3	4	5+	SUM
<b>People</b>						
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%

468

469 For the case study, as the 2001 census report did  
 470 not provide information related to the size and  
 471 number of bedrooms, the percentage in each  
 472 classification for 2001 is assumed to be the same as  
 473 that in 2011.  
 474

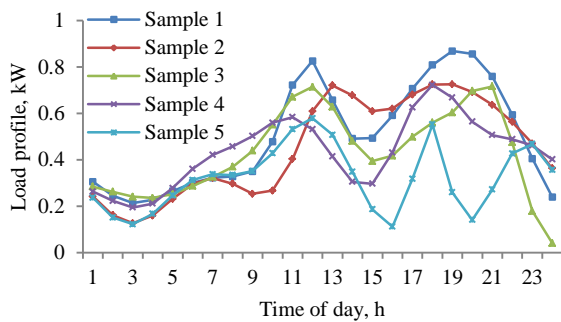
## 475 3.2 Results and validation

### 477 3.2.1 Examples of individual family household 478 load profile

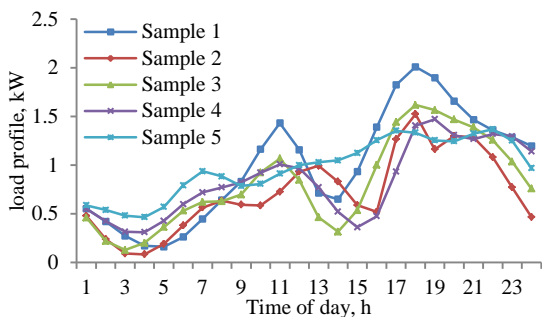
479 Ten load profile examples are shown in Figures 16  
 480 and 17. Figure 16 includes five examples of  
 481 electricity load of one person living in one bedroom.  
 482 Figure 17 shows results of five load profiles of  
 483 three persons living in two bedroom  
 484 accommodation. Each example is different because  
 485 of the random values used for Gaussian function



486 parameters  $b$  and  $c$ . But all ten results show  
 487 common characteristics of domestic load profile  
 488 which have two peak periods (morning and evening)  
 489 and variations before or after peak.



490  
 491 Figure 16: 5 Load demand profiles for 1 person in 1  
 492 bedroom accommodation  
 493



494  
 495 Figure 17: 5 Load demand profile of 3 persons in 2  
 496 bedroom accommodation  
 497

498 Comparison between Figures 16 and 17 shows the  
 499 peak loads have increased, as expected, with  
 500 changes in  $N_p$  and  $N_r$ . Figures 16 and 17 share  
 501 similar load characteristics to measurement results  
 502 in Figures 3 and 4, e.g. low activity level in early  
 503 morning and late evening, increase in electricity  
 504 demand during the two peak periods, etc.

505  
 506 **3.2.2 England and Wales national load model**  
 507 **results for Year 2001 and 2011**  
 508

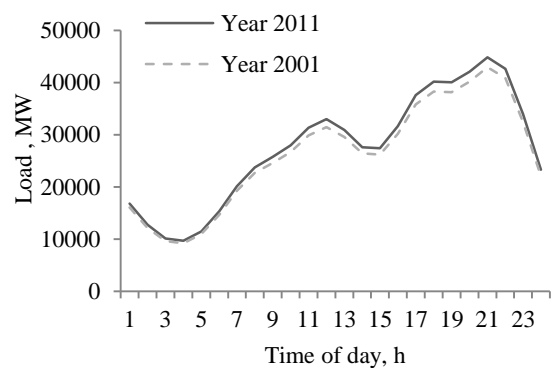
509 Modelling results of hourly domestic electricity use  
 510 in England and Wales in 2001 and 2011 are  
 511 presented in Figure 18. The model results for both  
 512 years have a very similar shape. The 2011 average  
 513 load magnitude increased smoothly between 7 a.m.  
 514 and 10 p.m. The mid-night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

518  
 519 This similar load changing character can also be  
 520 found in the England and Wales's national  
 521 electricity load (includes domestic, commercial and

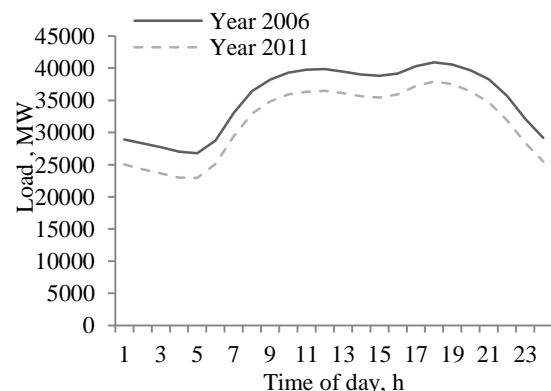
522 industry) in Figure 19, where the overall electricity  
 523 consumption behaviour did not change much over  
 524 the years. The mid-night load increase in Figure 19  
 525 is because many commercial and industrial energy  
 526 users still consumed electricity during the mid-  
 527 night time. Figure 19 also shows a decrease of  
 528 electricity load demand from 2006 to 2011. The  
 529 model, as shown in Figure 18, failed to represent  
 530 this decrease in electricity load demand. This is  
 531 because there is only one year's data on load  
 532 demand in relation to the number of occupant ( $N_p$ )  
 533 and bedrooms ( $N_r$ ) data used for load  
 534 characteristics analysis. This could be improved  
 535 when multiple years' average load becomes  
 536 available for load characteristics analysis.

537  
 538 The modelling results suggest that the population  
 539 and number of households have very little impact  
 540 on national domestic electricity load profiles in  
 541 terms of load shapes over the ten year period  
 542 investigated. Comparison of the modelling and real  
 543 data indicates that energy efficiency and other  
 544 measures have a much greater impact on energy  
 545 demand than population changes.

546



547  
 548 Figure 18: Modelling result of 2001 and 2011  
 549 England and Wales's electricity load.  
 550



551  
 552 Figure 19: England and Wales's national electricity  
 553 load 2006 and 2011 [19].  
 554

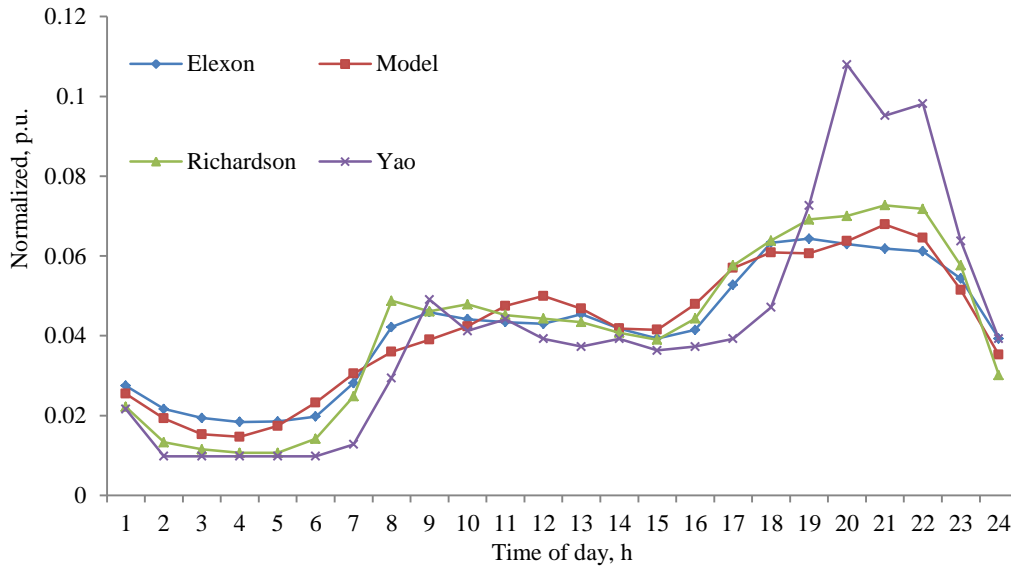


Figure 20: Result from present model, Yao model, Richardson model, and reference load from Elexon.

### 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.

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

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 Richardson'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.

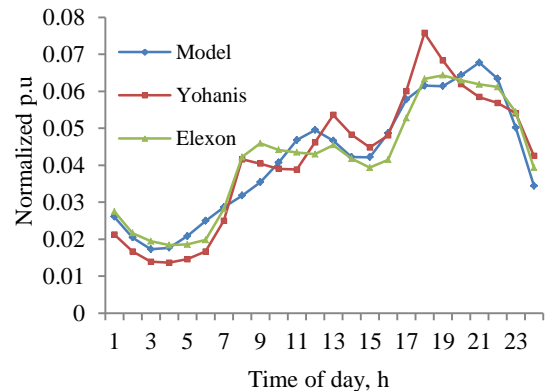


Figure 21: Yohanis study's average load profile in comparison to model result and Elexon's reference load.

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

#### 629 4. Conclusions and Discussions:

631 This paper introduced a novel method for  
632 determining regional electrical load through a  
633 minimum amount of information. The application  
634 of a multiple Gaussian function based method to  
635 model domestic household electricity load profile  
636 using the number of households in a region. Input  
637 data uses readily available information, or that  
638 which could be estimated for a proposed housing  
639 development, i.e. the number of persons  $N_p$  and  
640 bedrooms and  $N_r$  of the households. The presented  
641 model is based on Yohanis's domestic load profile  
642 characteristic study. Other domestic load studies  
643 based on measurement result with load changes per  
644 occupant and per bedroom can also serve the same  
645 purpose. Gaussian function curve fitting are used to  
646 analyse the load characteristic variation with  $N_p$ ,  
647  $N_r$ .

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

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

663 I) Improve domestic load profile characteristic  
664 study: i) The method will benefit from more  
665 detailed characteristic study, e.g. mid-day load  
666 change characteristics per occupant and per  
667 bedroom. ii) Increasing the number of households  
668 measured in the characteristic study will also

670 improve the model accuracy, e.g. the late morning  
671 peak in Yohanis's study leads to errors in the  
672 modelling result. iii) Better categorisation of the  
673 measured households could improve the model  
674 result, e.g. Yohanis's study only provided average  
675 load profile changes per occupants and bedrooms,  
676 by providing different type of household load  
677 profile changes per occupant and bedroom would  
678 improve the variety and accuracy of the model  
679 result. iv) Seasonal load profile change can be  
680 included in the model if each season's load change  
681 per occupant and per bedroom is provided in load  
682 characteristics study.

683 II) Further Gaussian parameters analysis: some  
684 Gaussian parameter relations to the  $N_p$  and  $N_r$   
685 require further investigation. i) The magnitude  
686 parameter values ( $a_2$ ,  $a_4$ ) drop at 3 person and 4  
687 bedrooms, shown in Figures 6 and 7. ii) The  
688 unusual duration parameter changes with three  
689 bedroom households in Figure 11. These indicate  
690 that certain types of family may require additional  
691 analysis. Increasing the number of data points for  
692 duration parameter will give a more complete  
693 picture of duration parameter characteristics and  
694 better analysis result.

#### 697 Reference:

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