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Review

A Rigorous Standalone Literature Review of Residential Electricity Load Profiles

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Abstract: The introduction of smart meters and time-use survey data is helping decision makers to understand the residential electricity consumption behaviour behind load profiles. However, it can be difficult to obtain the actual detailed consumption data due to privacy issues. Synthesising residential electricity consumption profiles may be an alternative way to develop synthetic load profiles that initially starts by reviewing the existing synthetic load profile methods. The purpose of this review is to identify the recent methods for synthesising residential electricity load profiles by conducting a rigorous standalone literature review. This review study has been applied and presented transparently and is replicable by other researchers. The review has answered the following research questions: the definition, concept and roles of residential electricity load profile and synthesised data; recent approaches and methods; research purposes; applicable simulations and validation methods of the final selected studies. The results show that the most applied approach in modelling residential electricity load profiles is the bottom-up approach. As it is detailed, it suitable to reflect the local residential behaviour in electricity consumption. Consequently, it is more complex to develop and calibrate the model as identified in the results. Bottom-up models are more powerful in analysing energy consumptions that focus on behavioural patterns, dwelling profiles and control strategies.

Keywords: rigorous; standalone literature review; load profiles; electricity consumption; domestic use; residential electricity consumption; top-down approach; bottom-up approach; statistical model; engineering model

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1. Introduction

The load profile analysis is essential in optimising and planning of the electricity distribution grid [1,2] and planning of the production capacity [1]. The term load profile has been used for decades in the field of energy, especially in the Demand-Side Management (DSM). In 1985, Gellings proposed the basic load profile shapes in DSM for electrical appliances [3]. A load profile can be defined as a pattern of how much electricity is used at each time presented in a graph. Narayan et al. in [4] defined “load profile as the power demand of an energy system mapped over time”, which not only identifies the energy demand but also plays an important role as a vital input to the electrical system design.

Responsible for 25% of the total energy consumption globally [2] in general, and a third of the final electricity in the European Union (EU) specifically [5] or 29% of the total electricity demand in Europe [6], the residential sector plays an important role in future electricity systems [6]. As it influences future electricity systems, the residential electricity load profile has a big role in capacity planning; In particular, it may improve the efficiency in the system operations, electricity grids and generation investments. In addition to capacity planning, the residential electricity load profile also plays a vital role in the energy market, included in analysing electricity tariffs, price structures, incentives, customer satisfaction and other economic optimisations. It may also support studies in renewable energy penetration, intelligent building and emissions reduction analyses. Furthermore, it is also important to have a high-resolution residential load profile in order to increase the share of "renewable energy feed-in, which is weather-dependent, intermittent and highly variable" [7].

A residential electricity load profile is defined as "a formal system that can reproduce the combined electricity consumption of all the electricity powered devices in a single/number of private/non-commercial residences" [5]. In modelling the residential sector, the standard load profile (SLP) is usually applied to model a household's load profile [5,6]. The standard electricity load profile is regularly identified by the distribution system operators (DSOs) or utility companies and is fundamental in their electricity grid planning [8]. Hence, rough estimations are employed with respect to the worst-case situations in modelling the residential load models [8]. However, there may only be a little amount of information about the nature of the load profiles on domestic electricity use in their typical data. Occupant behaviour that reflects a personal lifestyle varies widely and in unpredictable ways [9], and privacy issues are also a concern. Privacy issues are still the major challenge in successful energy data collection related to individual households. This nature of the load profile on the residential sector can impact energy use significantly by as much as 100% for a given dwelling [9]. Thus, the standard load profile might not be appropriate in a given planning decision-making process [1]. Therefore, a better presentation of the load profile is required that does not only support the utilities in planning their electricity network but also enhances customers' understanding of their electricity consumption if the data are available to them.

In line with this background, the ClairCity H2020 Project has the main aim to engage citizens in better understanding their environmental behaviours in a local context [10–16]. One way of gaining a deeper understanding of the residential electricity consumption behaviour is by synthesising the local load profiles. A simple review of load profile studies was presented in our previous work [2]. In this paper, it focuses on the recent residential electricity load profile methods, which limits the period to over the last decade, from 2010 to 2020. The purpose of focusing the review on the last decade is to have a recent overview and updates on the trends of the applicable methods in the field. This paper aims to answer the following questions:

1. What is the definition of the residential electricity load profile?
2. What is the definition of the synthesised load profile?
3. What are the roles of the residential electricity load profile?
4. What approaches and methods have been used to synthesise residential electricity load profiles in the last decade?
5. What are the purposes of synthesising residential electricity load profiles?
6. What inputs have been used to synthesise residential electricity load profile models?
7. How were the proposed models validated?
8. What are the strengths and weaknesses of these approaches?

A review study is an essential tool for analysing, summarising or synthesising the existing literature published in the applied energy field. Since literature reviews serve as "benchmarks" for other researchers in a specific field, they should cover the relevant literature to date and earn readers' confidence about the validity, reliability and relevance of their findings [17]. The review must be rigorously conducted to represent powerful information sources [17]. Therefore, in this work, a rigorous standalone literature review method has been selected and conducted in a transparent process, including presenting the challenges during this work. We agree with Cooper 2009 [18,19] that the review should be as transparent as possible, including explaining conflicting results. In line with the recent structural literature review development mentioned in [20], our analysis provides criteria, such as a research purpose and location, besides research methods, data description and validation. Previous works have reviewed electricity load profile studies, whereas our work applies the structure literature review method and is bound in scope to residential load profile studies in the last decade. Some of the extensive studies have discussed residential electricity load profiles using the data from smart meter [21–23], time-use survey (TUS) data [1,24,25] and synthesised data [25–31]. Smart meter data are the measured energy consumption data from installed advanced energy meters where the devices are integrated with computer sciences, advanced communication and measurement methods [32], while TUS data are the data from "time use surveys (TUS) measure the amount of time people spend doing various activities, such as paid work, household and family care, personal care, voluntary work, social life, travel, and leisure activities. The survey consists of a household interview, a personal interview, a diary and a week diary" [33]. The TUS data in [25] are used to create activity profiles.

In this work, we focused on the synthesised data, and some of the well-known load profile studies before 2011 were presented in [25–27]. According to the McGraw-Hill dictionary of scientific and technical terms, "synthetic data is any production data applicable to a given situation that are not obtained by direct measurement", while Nowok et al. 2016 in [34] defined synthetic data as artificially generated data that resemble the original (observed) data by preserving relationships between variables. In this study, synthesised data is defined as generated data. In essence, artificial data are used to represent real data according to what is the purpose of the synthesising process, which, in this case, is the residential electricity load profile. The synthesising process uses relevant variables where data pre-processing is required. The load profile study is conducted with two distinct approaches [2,4,29,35–38]: the bottom-up and the top-down approaches. The bottom-up approach estimates the energy consumption based on the data from individual users [39] and dwelling characteristics, and uses input data from a lower level, usually data at the appliance level. The bottom-up approach consists of two categories: statistical models and engineering models [9,39–41]. Statistical models calculate the dwelling energy consumption of the individual occupant, individual houses, a group of buildings, housing characteristics or a prototype of a building stock, which also can be extended to a bigger geographic area, such as a region or nation, using the representative weight of the sample [9,39,40], as applied in [2]. The model employs types of regression analyses, conditional demand analyses or neural networks [9,39,40]. Engineering models account for the building energy consumption based on building physical principles [39] and thermodynamic relationships [9] that require detailed physical variable data. The building's physical variables include geometry, envelope fabric, occupancy profiles, thermal profiles, indoor and outdoor temperatures, solar radiation, electrical appliances and so on [9,39,42].

In contrast, the top-down approach works on aggregate data that contain general information and statistics from large-area studies of electricity use but do not distinguish the individual user's consumption. This approach does not require a detailed profile of the buildings, appliances or end uses [40]. A top-down approach typically employs historical data with macroeconomic variables to estimate the total energy consumption in a residential sector [39,40]. Macroeconomic variables include employment rates, gender, gross domestic product (GDP) and price indices. In addition to macroeconomics, the historical data cover the climatic parameters, dwelling demolition rates, appliance ownership estimations and so on [9,39,40]. Furthermore, there are some models that employ both approaches to account for the energy consumption [9]; for instance, both approaches were applied in [2] to reflect the electricity load profile in a residential sector.

Thus, the purpose of this paper is to conduct a rigorous structured literature review and identify recent methods in synthesising residential electricity load profiles. The contributions of this work are: It provides a transparent process when applying a modified rigorous standalone literature review, and it becomes a source of knowledge in the residential energy demand area for new scholars and for those researchers outside the field. It also provides the recent methods in the last decade. The remainder of this paper is organised as follows: Section 2 presents the methodology of the rigorous standalone literature review. Section 3 describes the application of the modified rigorous standalone literature review from step 1 to step 5. Section 4 provides the discussion of step 6: Analysing and synthesising. Section 5 summarises and concludes the review, including the research implications for future work.

2. Methodology

A high-quality review means that the review is conducted rigorously. Rigor refers to the soundness of the research process, which has strong scientific and knowledge values [17]. One of the purposes of a standalone review, which is in line with our goal, is to identify the existing knowledge on a particular topic (Webster & Watson 2002; King & He 2005; Okoli & Schabram 2010 cited in [17]), especially the methods of synthesising residential electricity load profiles in the last decade. A framework in conducting a rigorous standalone review is required for our study. The framework provides high-quality and valuable information from past research that is useful as inspiration and useful for conducting our method in synthesising the residential electricity load profiles for the ClairCity [43] and CITIES Projects [44]. We then conducted our standalone review based on the modified set of guidelines for conducting a rigorous literature review that was proposed by [17] as follows:

1. Formulating the problem. Justifying the need of the review study, defining the review objective by identifying the research question and designing the concept of the synthesis are required in this basic stage [17]. As stated by Jessen et al. (2011) in [17], the entire study design is guided by the research questions. The research questions direct what type of information is needed and what information is to be searched.
2. Searching the literature. The searching is based on the guidance of the research questions. It is the fundamental part in the literature review before selecting and extracting data. Therefore, a specified strategy in searching the literature is required to identify the relevant studies and answer the research questions [17].
3. Screening for inclusion. In this stage, the set of rules includes the selection criteria [17,18,45,46], filtering criteria [18,47] and the final selected studies [17,18] being defined. It is the basic step for including and excluding specific studies [17], and it should be explicitly described how these procedures are conducted for ensuring transparency and replicability [19,46,48].
4. Assessing quality. The quality of the studies needs to be assessed after screening for inclusion. It is essential to assess whether the quality is affecting the results of the studies [17].
5. Extracting data. This step gathers the applicable information from the qualified studies, including how the primary studies were conducted and how the methods and the results were evaluated [17,49]. It includes defining what to capture and how it is captured [49,50], which helps to address the research question(s) [47].
6. Analysing and synthesising data. In the final stage, collation, summarising, aggregating, organising and comparing the evidence from the extracted studies are presented to provide a new contribution to the knowledge on a given topic. Finally, it is also expected to discuss the findings and present the conclusion in a meaningful way [17].

3. Results

The six steps of the applied rigorous standalone review method are presented in the following subsection, where the last step: Analysing and synthesising, is discussed in Section 4.

3.1. Formulating the Problem

It is challenging to sufficiently access detailed electricity consumption data in ClairCity case cities. An alternative is to develop synthesised data for each city. There are, however, different methods for developing a synthesised dataset, and hence, the objective of this work is to carry out a rigorous literature review of residential electricity load profile methods. This study evaluates the existing methods used to synthesise residential electricity load profiles and how they have developed in the last decade. This research question directs the entire study design, evaluates how the methods have evolved over the last decade and which type of method is most applicable for the ClairCity Project.

3.2. Searching the Literature

The review was done in the Scopus database, which is the largest scholarly database that indexes content from 25,000 active titles and 7000 publishers [51]. It is a fundamental step to define the relevant main phrases related to the existing residential electricity load profile methods. Therefore, three main phrases that have the same meaning were searched in the Scopus database: "Residential load profile", "Household load profile" and "Domestic load profile".

TITLE-ABS-KEY (domestic AND load AND profiles) OR TITLE-ABS-KEY (household AND load AND profiles) OR TITLE-ABS-KEY (residential AND load AND profiles) AND PUBYEAR > 2010 AND PUBYEAR < 2021.

The defined phrases made the searching process more specific, as it focused on the residential sector. The terms "energy use" or "energy consumption" were not selected as the defined phrases, since each of them had a broader coverage that could involve other sectors than residential electricity or other discussions than load profile terms. As a result, this query had 2221 related documents and contained about 150 indexed keywords. The 2221 initial results consisted of 1058 journal articles, 1111 conference papers, 23 book chapters, 19 reviews, 3 data papers, 2 books, 2 errata, 1 editorial and 1 letter.

3.3. Screening for Inclusion

In the screening stage, the criterion based on the language, publication stage, relevant keywords and relevant subject areas are defined below. The steps below are replicable and show the transparency of this review process.

3.3.1. Screening 1: Language

The first screening is the document's language. In this study, we defined English as the main universal language of science to be selected. As a result, in the 2221 documents, we had 2187 documents written in English. Other documents were eliminated: Chinese (18), German (6), Portuguese (4), Turkish (3), Russian (2), Spanish (2), French (1), Japanese (1), Korean (1) and Czech (1).

3.3.2. Screening 2: Publication Stage

The second screening is the documents' publication stage. The 2187 documents had 2174 documents in the final stage and 13 articles in press. In this stage, the results were reduced to 2174 documents.

3.3.3. Searching and Filtering: Keywords

As mentioned in the first phase, the results contained about 150 keywords, and similarly, they still had about 150 keywords at this stage. Therefore, filtering the irrelevant keywords was required. After eliminating about 100 keywords, there were 514 documents left.

3.3.4. Searching and Filtering: Subject Area

From the 514 documents, we filtered the irrelevant subject areas. In this case, the following subject areas: physics and astronomy, accounting, chemical engineering, earth and planetary sciences, agriculture and biological sciences, medicine, economics, biochemistry, art, health professions, immunology and microbiology, nursing, pharmacology, toxicology and psychology were eliminated from the list. We then had eight relevant subject areas at this stage: engineering, energy, computer science, mathematics, environmental science, materials science, social sciences and decision sciences. This filtering resulted in 404 documents.

3.4. Assessing Quality

From the 404 documents, we scoped our review to including only journal articles. Therefore, the number of documents was reduced to 177 journal articles. To ensure quality assurance, we limited our study to only peer-reviewed journals. The website of each journal was explored to check the peer-reviewing process. There were 83 journals listed at this stage. Additionally, as suggested by [20], the current impact of scholarly journals in the field was considered as a basis for selection. The Scimago rank of each journal was also visited to see the journal's metrics, and in some cases, it also announced the current status of the journal if it had been discontinued by Scopus. We eliminated 14 journals that consisted of 24 articles because of some reasons: They had no official website or were listed in a predatory journal or had been discontinued by Scopus. After this process, we only had 153 peer-reviewed articles. The next step was to revisit the title and abstract readings of each peer-reviewed article, and these two activities were done in one process per article. Abstract reading provided a clearer understanding and deeper assessment of the focus of the article [52]. They were then reduced to 43 peer-reviewed articles.

Lastly, full article reading was conducted for these 43 papers. Only papers that were focused on electricity load profiles in the residential sector were included. The research objective, methodology, data description and validation of the method were the focus of the article readings. The final collection was reduced to 31 peer-reviewed articles, as shown in Appendix A. Twelve of the listed articles were related to electric load profile studies. However, most of them focused on clustering profiles or the segmentation of the residential users that grouped customer profiles using existing data from smart meter, TUS or occupancy data [6,53–59], and one article characterised a seasonal variation using a monitored dataset [60]. Article [61] focused on the heating load profile in the United Kingdom, where it is not clear whether the heating used electrical appliances or gas or any other energy source of heating. Article [62] discussed a district cooling load profile, and article [63] focused on DSM. As mentioned in [64], domestic energy use can be categorised into thermal energy and electrical energy use for daily activities. However, as mentioned in [65], treating thermal and electrical systems as one is a substantial measure toward the integration of renewable power production. Our work is focused on electrical energy use load profiles in the residential sector, and therefore, we limited the scope to the articles that clearly mentioned the use of electrical appliances or electrical sources.

3.5. Extracting Data

In this stage, the relevant information from each primary study was gathered: the research objective, methodology, data description and validation method. The data extraction is displayed in Appendix B, which shows how the primary study was conducted. In addition, the mapping of the selected final articles is illustrated in Figure 1 to show an overview of the data extraction. The figure shows the approaches and methods applied in the studies.

The map shows the two categories of the load profile approach: top-down and bottom-up, where 30 articles applied the bottom-up approach and one article employed the top-down approach, as also shown in Table 1. The bottom-up approach consists of two methods: statistical and engineering. From the 30 articles, 25 articles applied the statistical method, such as the Markov model, fuzzy logic, neural network and autoregressive. The remaining five articles employed the engineering method based on partial differential equation (PDE), non-intrusive load monitoring (NILM) and home energy management systems (HEMS).

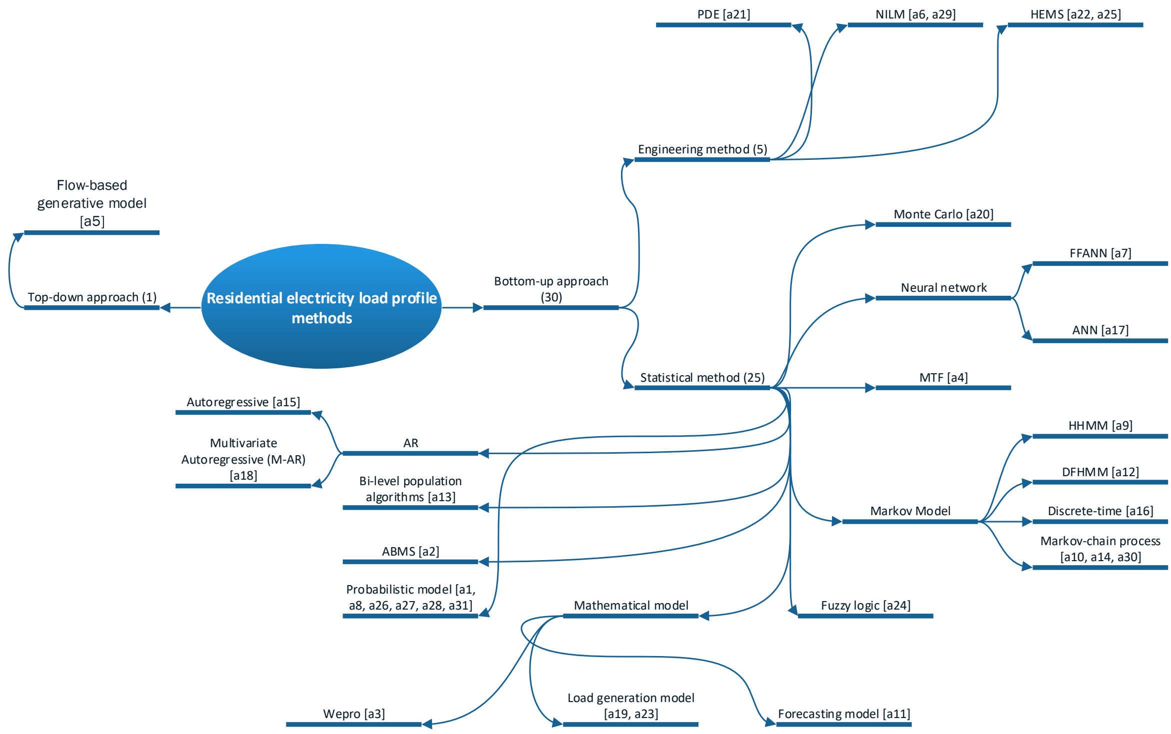

Figure 1. The approaches and methods map of the final selected articles. Thirty articles used the bottom-up approach, and one article used the top-down approach. See the article's ID in Appendix A.

Table 1. The approaches and methods applied in the final selected articles.

Approach	Number of Articles
Bottom-up	30
Statistical	25
Engineering	5
Top-down	1

Based on the mapping of the approaches and methods in Figure 1 and the list of final articles in Appendix A, we can identify the trend analysis of the method per year from 2013 to 2020, as shown in Table 2. This shows that the probabilistic and Markov chain models, which are the most employed models from the final articles, were applied throughout the years from 2011 to 2020 at the beginning, middle and end of the decade.

Table 2. Trend analysis of the method per year from 2013 to 2020.

Publication Year	Approach	Approach Category	Article	Probabilistic Model	Agent-Based Modeling and Simulation (ABMS)	Weighted Proportion	Multi-Tier Framework (MTF)	Flow-Based Generative Model	Non-Intrusive Load Monitoring (NILM)	Neural Network	Markov Model	Forecasting Model	Auto regressive (AR)	Load Generation	Monte Carlo	Partial Differential Equation (PDE)	Home Energy Management Systems (HEMS)	Fuzzy Logic	Bi-Level Algorithm
2020	Bottom-up	Statistical	a1	✓															
		Statistical	a2		✓														
		Statistical	a3			✓													
		Statistical	a4				✓												
2019	Top-down		a5					✓											
	Bottom-up	Engineering	a6						✓										
2018	Bottom-up	Statistical	a7							✓									
		Statistical	a8	✓															
		Statistical	a9								✓								
		Statistical	a10								✓								
		Statistical	a11									✓							
		Statistical	a12								✓								
2017	Bottom-up	Statistical	a13																✓
		Statistical	a14								✓								
		Statistical	a15										✓						

Table 2. *Cont.*

Publication Year	Approach	Approach Category	Article	Probabilistic Model	Agent-Based Modeling and Simulation (ABMS)	Weighted Proportion	Multi-Tier Framework (MTF)	Flow-Based Generative Model	Non-Intrusive Load Monitoring (NILM)	Neural Network	Markov Model	Forecasting Model	Auto regressive (AR)	Load Generation	Monte Carlo	Partial Differential Equation (PDE)	Home Energy Management Systems (HEMS)	Fuzzy Logic	Bi-Level Algorithm
2016	Bottom-up	Statistical	a16								✓								
		Statistical	a17							✓									
		Statistical	a18										✓						
2015	Bottom-up	Statistical	a19											✓					
2014	Bottom-up	Statistical	a20												✓				
		Engineering	a21													✓			
		Engineering	a22														✓		
		Statistical	a23											✓					
		Statistical	a24															✓	
		Engineering	a25														✓		
		Statistical	a26	✓															
		Statistical	a27	✓															
		Statistical	a28	✓															
2013	Bottom-up	Engineering	a29						✓										
		Statistical	a30								✓								
		Statistical	a31	✓															

4. Discussion

In this section, the merits and demerits of each approach, and method will be discussed. We will also present the data characteristics, validation and data quality scores of each article. The data extraction ended with 31 articles. As shown in Table 1, the majority of the final 31 studies employed the bottom-up approach, and only one study used the top-down approach. The bottom-up and top-down approaches are described explicitly in [2,4,29,35–38]. A combined bottom-up and top-down approach was employed in [2]. In fact, ref. [2] has also been included in the statistical bottom-up method category, as it used a statistical weighted proportion model and employed a detailed load model based on a load profile generator (LPG) [28,29,66] and artificial load profile generator (ALPG) [30,67].

The top-down approach was used in [68], where it employed a machine learning method based on flow-based generative models. A daily forecast scenario was generated by the observed data from the previous day as the historical input data with hourly resolutions. The simulation was done for 105 households in Austin, Texas, USA. The validation of the results was compared with the observed data generated during data training and within the aggregated load profiles. The merit of using flow-based generative models is that they may provide a set of scenarios that are able to cover a wide range of behaviours that are more accurate for residential loads at different aggregation levels. Specifically, the model uses a reversible transformation flow to optimise the value of the conditional density function of future loads based on historical observations [68]. However, in certain cases, if the conditioned historical observations are too noisy, the simulations show failed results when forecasting accurate future loads, because they cannot provide useful side information for the models [68]. Five of the thirty articles used bottom-up engineering methods, namely PDE [69], NILM [38,70] and HEMS [71,72]. Most of these engineering method studies used appliance usage as the main input data [38,70–72] and thermal behaviour [69] for a case of modelling a single appliance load profile: an electric water heater.

The merits of the PDE physics-based method in [69] were dedicated to modelling the dynamic behaviour of an electric water heater. The results showed accurate and realistic temperature variations under different operation modes. The simulation was done in hourly resolutions, and the results were compared with field measurement data. However, it requires better algorithms and parallel computing techniques to speed up the computation of the model. This computational speed issue was also addressed by [2], where it was important to identify the processing time in the case of a model's efficiency. For instance, the ALPG model [30] specified the drawback of its performance where the tool was used for one simulation with a maximum of 100 households. Computational speeds and technical requirements that are used to run the models need to be specified, as informed in [2,69,70,73].

The NILM-based method in [70] employed an additive factorial approximate maximum a posteriori (AFAMAP) based on iterative fuzzy c-means (IFCM) to solve load disaggregation. The proposed model outperforms the latter when more electrical appliances work simultaneously. However, the model requires improvement to solve load disaggregation problems in the case of real-time scheduling at a high frequency. A different NILM-based study to solve load disaggregation was also presented in [38]. It used on/off algorithm state models, as well as multi-state models, to disaggregate the operation and the power consumption of each model, where it presented a truth table matrix and a matching process. The improvement of this model was required to disaggregate the continuous variable appliances and identical power consumption appliances due to the possibility of profile duplication among the electrical appliances [38]. Both of the NILM-based methods in [38,70] simulated the load profiles in one-minute resolutions and validated the results by comparing them with another model's results or experiment's results.

Another method is the HEMS-based method, where it uses energy management devices at the appliance level [71,72]. The advantage of this HEMS-based method in [71] was that the operation of a single appliance could be controlled for an emerging demand response program with high-resolution data. However, the improvement of this method is still required to cover the account for the load priority and customer comfort by developing a more intelligent HEMS algorithm. While the merit of the HEMS-based method in [72] was the time variation profile of energy that agreed with the merit in [2], where the results could produce a time division analysis based on the seasonal variations, monthly variations, typical seasonal days and hourly variations.

The HEMS-based methods were simulated in two houses [71] and forty single family homes [72], where both cases were conducted in the United States. Unfortunately, no validation was is provided in [71], but validation by comparing the results with other measured data was performed in [72]. Most of the engineering methods in the final selected articles are applicable to analyse the load profiles of multi-appliances. These engineering-based studies were conducted in the United States [70–72], Korea [38] and Canada [69].

The statistical bottom-up method was applied in 25 studies, including Markov models [29,73–77]. The psychological model was applied in [28], where the model was able to simulate the behaviour of each of the household's occupant(s). As this model has a greater level of detail that is similar to all of the statistical bottom-up methods applied in [29,73–77], it is very flexible for simulating the variations in the behaviours of different occupants in different households. The Markov models in [73] employed a hierarchical hidden Markov model (HHMM), and [74] used a disaggregation approach based on the difference factorial hidden Markov model (DFHMM) and the Kronecker operation. Another method in [75] used a discrete time Markov model that was controlled by a nonhomogeneous poison process (NHPP model). Lastly, the Markov chain process was used in [76], where it employed the high-resolution probabilistic model CREST, an integrated thermal–electrical demand model [31], and in the LPG [29], and LPG was also employed in [77]. Major advantages of the combined Markov model in [74] were the modelling simplicity and inference, as well as load detection efficacy using general historical information in the presence of perturbations. A statistical method is applied in [73], where the hierarchical hidden Markov model (HHMM) fits a single-mode appliance by being able to distinguish the standby mode from the off mode, while, for the multi-mode appliances, the simulation showed a more accurate result than the conventional hidden Markov model (HMM). Another statistical bottom-up method applied in [75] showed a great advantage in flexibility to reflect any specific load profile scenario based on different regions and the potential to control individual low-voltage loads by turning on the activation function of the corresponding load model. Furthermore, a trimodal Gaussian mixture model in [76] showed a valued estimate of the observed distribution of the total annual consumptions. This model can overcome the complexity of distribution with the diversity of real-life households. However, future research is required to identify the resultant composite distribution, as it does not exhibit normal features, whether it is a trend or a coincidence. The current underlying assumptions about electricity consumption with limited variability need to be rectified in order to gain a better interpretation of the characteristics of the measured data. In accordance with [75], the flexible demand response (DR) model in [77] can be applied in any region under any energy scenario. It is a more comprehensive model that considers the various electrical appliances and comfort levels of customers. Another advantage to this model is that a genetic algorithm was developed to control the operation of the appliances based on real-time electricity prices in order to achieve cost reduction without disregarding the level of satisfaction and comfort. The applicable methods in [71,77] are concerned with maintaining customer comfort preferences.

Furthermore, a fuzzy logic model in [78] was applied with the main advantage that it minimises the risk inherent when DSM strategies are designed. It also allows the inclusion of key human behaviour characteristics that influence the use of electrical appliances. Another advantage of the proposed model is requiring limited or little input and expert knowledge to form the activation profiles of the electrical appliances compared to other approaches that require huge amounts of input data. An improvement in the proposed model is needed to model human behaviour, since the shape of load curves is influenced by the occupants' behaviour. In this case, it is recommended to see the psychological model proposed in [28].

Autoregressive models were applied in [79,80]. In [79], some models: flat forecast, persistent forecast, feed forward neural network, Gaussian–Markov model and ARIMA model were developed to allow a more reliable scheduling of the grid. The ARIMA model has the advantage of providing a more accurate forecast at a higher computational expense, while the Gaussian–Markov model provides almost equivalent levels of accuracy to the ARIMA model but at a lower computational expense. It also takes into account the model scalability or reduced computing processing, as addressed in [2,69,70,73]. The improvement of the models is necessary in the choice of constituent forecasts by weighting model outputs according to the time of day. The autoregressive model in [80] was developed to improve the forecast for short-term load profiles. Similar to [2], the model also provided a load profile based on a time division concept—in this case, weekday and weekend. Another work was needed to develop an algorithm for longer prediction horizons and comprehensive dwelling information, such as location, number of floors and occupancy profiles. A unique hierarchical, multi-scale and multi-resolution using a multi-layer architecture framework was developed in [81]. The proposed model showed merit flexibility in modelling large-scale neighbourhoods and at the detailed appliance level. It supported effective energy planning, future energy demand estimations and a complex and dynamic analysis of consumer behaviour. This study also covered a load profile based on the time division concept, as discussed in [2,72,79]. However, a high-performance distributed platform is required in forecasting a load profile at the appliance level.

The multi-tiered framework in [4] showed several advantages in scalability and adaptability for specific regions and communities that reflect the local measured or desired electricity consumption data. However, there is a constraint at the appliance level: only the fridge is treated as a special case at the moment, which should be expanded to other appliances. Neural network methods were applied in [82,83], where they showed merit in the forecasting capability and reliability of the models. The proposed model in [82,83] focused on small microgrids and residential load levels. Improvement is necessary to cover the real-time pricing that usually changes on an hourly basis [82], while [83] proposed an improvement to enhance the forecasting capability in relation with renewable energy production and energy storage.

A method in [84] consisted of two embedded optimisation problems where it modelled a bi-level problem, which is a relation between retailers and consumers where the retailer is the leader and the consumer is the follower. The proposed model showed merit in comprehensive and detailed solutions for lower-level problems, since it offers multiple alternative optimal solutions. A further improvement is suggested to provide an explicit objective function that may assess consumer discomfort in relation to load scheduling, which can increase the complexity of the model. Furthermore, a weighted proportion model in [2] was found to be simpler and more efficient in the case of computational speed. This method creates efficiency in the size and storage of generated load profile files. It also shows merit in reflecting the local characteristics of the residential sector based on time variation analyses: seasonal analysis, monthly analysis, daily analysis and hourly analysis. However, the model relies on the profile generator as the external tool to match the weighted profile with the representative occupants' profiles.

A quantitative simulation model based on the Monte Carlo approach was employed in [85]. The assumption applied in the model was that the electricity use consisted of three different modules: the usage of electrical appliances, domestic hot water (DHW) consumption and space heating. The simulation results showed that the model could reflect the realistic local power demand profiles for the households living in detached houses. However, the model limited the appliances only to the predefined electrical appliance setup. As the behavioural model was very detailed and complex, the proposed model applied the constant behaviours of the household members. The other methods employed load generation models [36,86], a forecasting model [87] and probabilistic models in [35,37,88–91].

In general, the merits and demerits of the method, whether it is the top-down or bottom-up approach, are specified in Table 3. According to [9,41,86,92], the limitation of bottom-up models is that those models typically require a lot of detailed information, such as that presented in Appendix B, where the models required input about occupancy, behavioural, appliances, climate, dwelling and socioeconomics data. It makes the data collection process more time-consuming and costly. Consequently, it is more complex to develop and calibrate the model as identified in the results (Articles a1 to a4 and a6 to a31 in Appendix A).

Table 3. Strengths and weaknesses of the approaches.

Approach	Strengths	Weaknesses
Top-down	• Data collection is limited, easier and usually available. • Suitable for long-term changes and energy transition purposes. • Simple calculation.	• Relies on historical data. • Inherent capability to model discontinuous advances in technology. • Lack of detailed data resulting in less flexible calculation.
Bottom-up	• Detailed information and results. • Higher prediction capability and accuracy. • Ability to account for more objectivity in relation with energy consumption. • Strong in behavioural aspects, dwelling profiles and control strategies. • The results can be extrapolated to higher level: region or national level.	• Requires more inputs; relies on more detailed dwelling information. • Data collection processes can be costly. • Data collection and calibration process are usually time consuming. • More complex simulation. • Higher levels of expertise required in the development and use of the EM.

The advantage of the bottom-up approach is that, as it is detailed, it can analyse the customised purpose of load profile calculations, as in articles a1 to a4 and a6 to a31 in Appendix A. For instance, as described in [86], bottom-up models can investigate the effect of a single appliance on the total load. This basic analysis supports the future study of smart grids. In line with [41], bottom-up models are more powerful in analysing energy consumptions that focus on behavioural patterns, dwelling profiles and control strategies. Although this approach typically requires detailed inputs, it can calculate the total residential energy use without relying on historical data. In addition, the results can be extended to higher levels in the scope of top-down models: the regional or national level, as mentioned before in [9,39,40].

In the case of the top-down approach, one of its limitations is that it relies on historical data, although these data are usually available and easier to find [9]. The reliance on historical data makes it less flexible and less capable to model discontinuous advances in technology. As shown in [68], the sole article that employed the top-down approach, historical data were used as the data input. As mentioned, the applicability of this approach is simpler than the bottom-up approach, as it requires limited information, which is easier to find. Those models also perform simpler calculations than the bottom-up models. Top-down models are suitable to account for the long-term energy consumption or energy transitions within the residential sector.

Therefore, based on our work, the most suitable approach that is in line with our project to reflect the local residential behaviour is the bottom-up models. Specifically, for energy use calculations in relation with new technologies or building profiles, the bottom-up engineering models are recommended due to requiring high levels of expertise.

Moreover, the research objective of each study was identified to gain an overview of their specific purpose in relation with the residential electricity load profile. The research objectives of the 31 articles were group into 12 categories based on specific aspects: flexibility profiles of the individual technology [88], multi-resolutions or different load profile resolutions [81], electricity access [4], a forecasting scenario [68], electricity costs [77] and a comparison study between the synthesised and metered data [76]. Several studies had a similar main purpose in developing the cities' or districts' load profiles [2,90] and load disaggregation [38,70]. There were four big groups of the studies that addressed the purpose of short-term load forecasting [79,80,83,93], residential consumption behaviour [29,35,37,75,84,87], appliance usage [69,72–74,91] and residential buildings [36,71,85,86]. Most of the engineering-based studies addressed the purpose in relation with load disaggregation [38,70] and appliance usage [69,72]. The research purpose about load disaggregation is typically conducted with the NILM-based method, as presented in [38,70].

In the case of data characteristics, most of the input data used in the statistical-based studies covered behavioural aspects that could be related to the occupants and/or appliances, including the household profiles, appliance usage and occupancy profiles. Some studies combined these parameters with climate parameters, such as outdoor temperature [2,29,77,80]. Thermodynamical aspects were added to the input data in [85,90]. The load profile time resolutions in the statistical method studies were generated from high-resolution data that were mostly in hourly and one-minute resolutions. A quarter-hour resolution profile was generated in [84].

Most of their validations were conducted by comparing the results with measured data [2,4,29,35,75,76,85–88] or load profiles from other projects [36,37,78,89,90] using the performance metrics [73,74,79,81,83,93] and employing a certain algorithm [77,84]. A combination of the measured data and performance metrics was used for validation in [80]. Validation with real data is still a major challenge in most related studies, since privacy issues are the main concern. Applications of the methods were performed in two example cases [91] without explicitly describing the validation method. As mentioned, most of these statistical-based studies were applied to more than one appliance or multi-appliances. Similarly, with the engineering-based studies, there was also a study specifically focused on a single appliance: electric space heaters [74]. In contrast to the engineering-based group, where all of them focused on the appliance level, in the statistical-based group, most of the studies focused on a bigger scope: household, neighbourhood or local levels. A few of them were focused on the appliance level [73,74,78,84]. The countries that have conducted or simulated most of the statistical studies in the final list are Germany [2,29,88] and Spain [37,78,89], followed by the United Kingdom [76,79] and Brazil [75,77], although in six of the thirty-one studies, it was not mentioned where the studies were conducted. The remaining studies were from Pakistan [81], Rwanda [4], Italy [90], Singapore [86], the United States [80], Iran [35], Portugal [83] and Sweden [85]. Specifically for the study in [2], it was simulated for an Amsterdam case study using the simulators LPG developed in Germany and ALPG developed in the Netherlands. In general, whether it is a top-down or a bottom-up approach, all studies have produced temporal resolution data. Additionally, the analysis in [80] was extended to a spatial analysis due to air conditioner (AC) loads' strong dependency on the weather parameters and high interhouse correlations. In addition, the top five cited articles of the final list were identified in Scopus on 1 April 2021 as follows: [69,71,79,80,86].

Furthermore, in order to quantify the quality of information in relation to the research questions of this study, a basic data quality score was created. It comprised 11 measurable attributes, as shown in Table 4. The availability of each attribute in the final articles is uniformly weighted, where each attribute gets one score. Table 4 shows the distribution scores for the 31 final articles. It is shown that 24 articles addressed all eleven attributes, which are recommended to be in the priority review list. Another four articles get a 10 score, because it was not clearly identified where the case study's location was or the simulation's country or region. The case study's location might be a minor issue. However, it is still essential to recognise the simulation's location in order to gain a better understanding of the data characteristics and the developed model. For instance, it was found out in a3 [2] that the ALPG model [30,67] was developed based on the Dutch dwelling system. Thus, when it is applied in the Netherlands' case study, the result is according to the Dutch real electricity consumption data. The other two articles (a26 and a31) that get a 10 score did not specify the number of simulated dwellings or households. The lowest score was article a28 that had an 8 score, because it did not clearly mention the number of simulated dwellings or households or how the applied method was validated, and it also did not mention the countries or regions of the simulation. In general, the results showed that about 77% of the final articles addressed all the required information to answer the research questions in this study.

Table 4. Basic data quality score of the final articles.

Article ID	Objective	Approach	Method	Merits	Demerits	Model's Input	Time Resolution	Number of Simulated Dwellings/Households	Validation	Model's Scale	Country/Region	Score
a1	1	1	1	1	1	1	1	1	1	1	1	11
a2	1	1	1	1	1	1	1	1	1	1	1	11
a3	1	1	1	1	1	1	1	1	1	1	1	11
a4	1	1	1	1	1	1	1	1	1	1	1	11
a5	1	1	1	1	1	1	1	1	1	1	1	11
a6	1	1	1	1	1	1	1	1	1	1	1	11
a7	1	1	1	1	1	1	1	1	1	1	1	11
a8	1	1	1	1	1	1	1	1	1	1	1	11
a9	1	1	1	1	1	1	1	1	1	1	1	11
a10	1	1	1	1	1	1	1	1	1	1	1	11
a11	1	1	1	1	1	1	1	1	1	1	0	10
a12	1	1	1	1	1	1	1	1	1	1	0	10
a13	1	1	1	1	1	1	1	1	1	1	0	10
a14	1	1	1	1	1	1	1	1	1	1	1	11
a15	1	1	1	1	1	1	1	1	1	1	1	11
a16	1	1	1	1	1	1	1	1	1	1	1	11
a17	1	1	1	1	1	1	1	1	1	1	1	11
a18	1	1	1	1	1	1	1	1	1	1	1	11
a19	1	1	1	1	1	1	1	1	1	1	1	11
a20	1	1	1	1	1	1	1	1	1	1	1	11
a21	1	1	1	1	1	1	1	1	1	1	1	11
a22	1	1	1	1	1	1	1	1	1	1	1	11
a23	1	1	1	1	1	1	1	1	1	1	0	10

Table 4. *Cont.*

Article ID	Objective	Approach	Method	Merits	Demerits	Model's Input	Time Resolution	Number of Simulated Dwellings/Households	Validation	Model's Scale	Country/Region	Score
a24	1	1	1	1	1	1	1	1	1	1	1	11
a25	1	1	1	1	1	1	1	1	1	1	1	11
a26	1	1	1	1	1	1	1	0	1	1	1	10
a27	1	1	1	1	1	1	1	1	1	1	1	11
a28	1	1	1	1	1	1	1	0	0	1	0	8
a29	1	1	1	1	1	1	1	1	1	1	1	11
a30	1	1	1	1	1	1	1	1	1	1	1	11
a31	1	1	1	1	1	1	1	0	1	1	1	10

The challenge of this applied approach lies in the searching and filtering stages, because it depends on the selected search engine system. The process of removing the non-relevant keywords or subject areas may dismiss a potentially relevant article. An example: while analysing and synthesising the final 31 articles, the article [31] about the new CREST model was read as part of [76], because CREST's electric load model was used in [76]. As the title of article [31] was "High-resolution stochastic integrated thermal–electrical domestic demand model", then it should be on the list of final articles. Similarly, Ref. [64] was read as part of [88], since the synPRO model proposed in [64] was used in [88]. The title of [64] was "Model for electric load profiles with high time resolution for German households". In fact, both of the examples were listed in the initial searched results but were not included in the final articles.

5. Conclusions

A review according to the rigorous standalone literature method was applied and presented in a transparent way and is replicable by other researchers. The method helped to gather, analyse and synthesise recent articles in relation to residential electricity load profiles. This study answered all the research questions focused on the research purpose, approach, method, data description, applicable simulation and validation.

The term load profile was used in this study, which has been used for decades in the DSM field. The results showed that the three defined phrases that have the same meaning: "residential load profile", "household load profile" and "domestic load profile" contribute to making the searching process more focused and specific. It also indicates that the most applied approach in the last decade has been the bottom-up approach with statistical-based methods. It is concluded that the most suitable approach that is in line with the purpose to reflect local residential behaviour is the bottom-up models. In this study, the most common research purpose addressed by the major studies was to analyse residential consumption behaviours. The research purposes in relation to the short-term load forecasting, appliance usage and residential buildings have also become important topics in some studies.

In most cases, privacy issues are still the important challenges in load profile studies. This study helps policy makers gain a better understanding of local residential load profiles in electricity consumption. The review results in this study help to identify which approach and method are suitable to represent the local residential electricity load profile based on a specific purpose. This study also supports decision makers in making more effective and more cost-efficient policies in relation to green transitions at the local level. This review was done in the Scopus database, and it would be interesting to apply this review method to two databases, e.g., Scopus vs. WoS, and compare the results. It could overcome the challenge of a sensitive case during the searching and filtering process in this study, because the sensitivity case may depend on the selected search engine database.

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Appendix A

ID	Article's Title
a1	Fischer, D.; Surmann, A.; Biener, W.; Selinger-Lutz, O. From residential electric load profiles to flexibility profiles—A stochastic bottom-up approach. *Energy Build.* **2020**, *224*, 110133.
a2	Mahmood, I.; Quair-tul-ain; Nasir, H.A.; Javed, F.; Aguado, J.A. A hierarchical multi-resolution agent-based modeling and simulation framework for household electricity demand profile. *Simulation* **2020**, *96*, 655–678.
a3	Kewo, A.; Manembu, P.D.K.; Nielsen, P.S. Synthesising residential electricity load profiles at the city level using a weighted proportion (wepro) model. *Energies* **2020**, *13*.
a4	Narayan, N.; Qin, Z.; Popovic-Gerber, J.; Diehl, J.C.; Bauer, P.; Zeman, M. Stochastic load profile construction for the multi-tier framework for household electricity access using off-grid DC appliances. *Energy Effic.* **2020**, *13*, 197–215.
a5	Zhang, L.; Zhang, B. Scenario frecasting of residential load profiles. *arXiv* **2019**, *38*, 84–95.
a6	Ji, T.Y.; Liu, L.; Wang, T.S.; Lin, W.B.; Li, M.S.; Wu, Q.H. Non-Intrusive Load Monitoring Using Additive Factorial Approximate Maximum a Posteriori Based on Iterative Fuzzy c-Means. *IEEE Trans. Smart Grid* **2019**, *10*, 6667–6677.
a7	Ebrahim, A.F.; Mohammed, O.A. Pre-processing of energy demand disaggregation based data mining techniques for household load demand forecasting. *Inventions* **2018**, *3*.
a8	Sepehr, M.; Eghtedaei, R.; Toolabimoghadam, A.; Noorollahi, Y.; Mohammadi, M. Modeling the electrical energy consumption profile for residential buildings in Iran. *Sustain. Cities Soc.* **2018**, *41*, 481–489.
a9	Kong, W.; Member, S.; Dong, Z.Y.; Member, S.; Hill, D.J.; Fellow, L.; Ma, J.; Zhao, J.H.; Luo, F.J. A Hierarchical Hidden Markov Model Framework for Home Appliance Modeling. **2018**, *9*, 3079–3090.
a10	Veras, J.M.; Silva, I.R.S.; Pinheiro, P.R.; Rabêlo, R.A.L. Towards the handling demand response optimization model for home appliances. *Sustain.* **2018**, *10*, 1–18.
a11	Gao, B.; Liu, X.; Zhu, Z. A bottom-up model for household load profile based on the consumption behavior of residents. *Energies* **2018**, *11*.
a12	Henao, N.; Agbossou, K.; Kelouwani, S.; Hosseini, S.S.; Fournier, M. Power estimation of multiple two-state loads using a probabilistic non-intrusive approach. *Energies* **2018**, *11*, 1–15.
a13	Carrasqueira, P.; Alves, M.J.; Antunes, C.H. Bi-level particle swarm optimization and evolutionary algorithm approaches for residential demand response with different user profiles. *Inf. Sci. (Ny).* **2017**, *418–419*, 405–420.
a14	Ramírez-Mendiola, J.L.; Grünewald, P.; Eyre, N. The diversity of residential electricity demand—A comparative analysis of metered and simulated data. *Energy Build.* **2017**, *151*, 121–131.
a15	Stephen, B.; Tang, X.; Harvey, P.R.; Galloway, S.; Jennett, K.I. Incorporating practice theory in sub-profile models for short term aggregated residential load forecasting. *IEEE Trans. Smart Grid* **2017**, *8*, 1591–1598.
a16	Casella, I.R.S.; Sanches, B.C.S.; Filho, A.J.S.; Capovilla, C.E. A Dynamic Residential Load Model Based on a Non-homogeneous Poisson Process. *J. Control. Autom. Electr. Syst.* **2016**, *27*, 670–679.
a17	Journal, P.Q.; Rodrigues, F.; Cardeira, C.; Lisboa, U. De Energy Household Forecast with ANN for Demand Response and Demand Side Management. **2016**, *1*, 2–5.
a18	Tascikaraoglu, A.; Sanandaji, B.M. Short-term residential electric load forecasting: A compressive spatiooral approach. *Energy Build.* **2016**, *111*, 380–392.
a19	Chuan, L.; Ukil, A. Modeling and Validation of Electrical Load Profiling in Residential Buildings in Singapore. IEEE Trans. *Power Syst.* **2015**, *30*, 2800–2809.
a20	Sandels, C.; Widén, J.; Nordström, L. Forecasting household consumer electricity load profiles with a combined physical and behavioral approach. *Appl. Energy* **2014**, *131*, 267–278.
a21	Xu, Z.; Diao, R.; Lu, S.; Lian, J.; Zhang, Y. Modeling of electric water heaters for demand response: A baseline PDE model. *IEEE Trans. Smart Grid* **2014**, *5*, 2203–2210.

ID	Article's Title
a22	Pipattanasomporn, M.; Kuzlu, M.; Rahman, S.; Teklu, Y. Load profiles of selected major household appliances and their demand response opportunities. *IEEE Trans. Smart Grid* **2014**, *5*, 742–750.
a23	Abdelsalam, A.A.; Gabbar, H.A.; Musharavati, F.; Pokharel, S. Dynamic aggregated building electricity load modeling and simulation. *Simul. Model. Pract. Theory* **2014**, *42*, 19–31.
a24	Zúñiga, K. V.; Castilla, I.; Aguilar, R.M. Using fuzzy logic to model the behavior of residential electrical utility customers. *Appl. Energy* **2014**, *115*, 384–393.
a25	Cetin, K.S.; Tabares-Velasco, P.C.; Novoselac, A. Appliance daily energy use in new residential buildings: Use profiles and variation in time-of-use. *Energy Build.* **2014**, *84*, 716–726.
a26	Ortiz, J.; Guarino, F.; Salom, J.; Corchero, C.; Cellura, M. Stochastic model for electrical loads in Mediterranean residential buildings: Validation and applications. *Energy Build.* **2014**, *80*, 23–36.
a27	Santiago, I.; Lopez-Rodriguez, M.A.; Trillo-Montero, D.; Torriti, J.; Moreno-Munoz, A. Activities related with electricity consumption in the Spanish residential sector: Variations between days of the week, Autonomous Communities and size of towns. *Energy Build.* **2014**, *79*, 84–97.
a28	Gruber, J.K.; Jahromizadeh, S.; Prodanović, M.; Rakočević, V. Application-oriented modelling of domestic energy demand. *Int. J. Electr. Power Energy Syst.* **2014**, *61*, 656–664.
a29	Park, H. Load profile disaggregation method for home appliances using active power consumption. *J. Electr. Eng. Technol.* **2013**, *8*, 572–580.
a30	Pflugradt, N.; Teuscher, J.; Platzer, B.; Schufft, W. Analysing low-voltage grids using a behaviour based load profile generator. *Renew. Energy Power Qual. J.* **2013**, *1*, 361–365.
a31	Caputo, P.; Gaia, C.; Zanotto, V. A methodology for defining electricity demand in energy simulations referred to the italian context. *Energies* **2013**, *6*, 6274–6292.

Appendix B

ID	Approach	Method	LP's/Model's Input	Time Resolution	Number of Simulated Dwelling(s), hh(s)	Validation	Model's Scale	Country
a1	Bottom-up: Statistical	Physical and behavioural model	Behavioural, relevant technology, diversity in sizing and controller settings	One-minute	1555 MFH and SFH	Compared with the measured data	Household level	Germany
a2	Bottom-up: Statistical	a multi-resolution agent-based modelling and simulation (ABMS) framework	Neighbourhood, social and appliances	One-minute	264 houses	Performance metrics: MAD, RMSE, MAPE%, CV(RMSE)	Local (neighbourhood)	Pakistan
a3	Hybrid: Combination of top-down and bottom-up: Statistical	Weighted proportion	People behaviour, climater parameters, appliance usage	Hourly	5 household profiles	Measured data: NEDU	Local (City)	The Netherlands Germany
a4	Bottom-up: Statistical	Stochastic model	Type of the off-grid appliances, power rating, quantity, and other operating constraints	One-minute	5 households: tier 1-tier 5	Measured data: SHS	Household level	Rwanda
a5	Top-down	Machine learning (Deep): flow-based generative models	Historical data	Daily based on previous day hourly resolution	105 households	Compared with the realized data generated in data training and the aggregated load profiles	Single household, neighbourhood level	United States
a6	Bottom-up: Engineering	additive factorial approximate maximum a posteriori (AFAMAP) based on iterative fuzzy c-means (IFCM)	active and reactive power as input	Minutely	A single household	Compared with other models: Hart's and bivariate	Household at appliance level	Canada

ID	Approach	Method	LP's/Model's Input	Time Resolution	Number of Simulated Dwelling(s), hh(s)	Validation	Model's Scale	Country
a7	Bottom-up: Statistical	Feed-Forward Artificial Neural Network	Aggregated power consumption for the home: current and historical consumption hours	Hourly	2 houses-dataset from UKDALE	Performance metrics: RMSE, NRMSE, MAE	Single household	Not specified
a8	Bottom-up: Statistical	probability density function (PDF)	Behavioural	One-minute	149 residences	compared with the measured profile	Single and local level	Iran
a9	Bottom-up: Statistical	Hierarchical hidden Markov model (HHMM)	Appliance behaviour	One-minute	7 appliance types: 30 generated cases	Evaluation metric formula	Appliance level	Not specified
a10	Bottom-up: Statistical	Mathematical optimization model	Behavioural, climate and price	Hourly	10 households	Genetic algorithm	Household level	Brazil
a11	Bottom-up: Statistical	Forecasting model	Behavioural	Hourly and daily	64 households	Measured data	Local level	Not specified
a12	Bottom-up: Statistical	disaggregation approach based on the difference factorial hidden Markov model (DFHMM) and the Kronecker operation	Usage of appliance	Minutes	Appliance data: ECO dataset	Metric evaluation	Appliance level	Not specified
a13	Bottom-up: Statistical	Two bi-level population-based algorithms	Usage of appliance	15 min quarter-hour	Appliance data: actual audit information	compared with the existing hybrid algorithm: HBLEA	Appliance level	Not specified
a14	Bottom-up: Statistical	high-resolution probabilistic model	Occupancy profiles	One-minute	22 households	Compared with the measured data	Household level	United Kingdom
a14	Bottom-up: Statistical	Autoregressive (AR) models	conventional stationary regression time series	Hourly	5 households	Error metrics: MAE, MAPE, Permutated 4-Norm	Household level	United Kingdom

ID	Approach	Method	LP's/Model's Input	Time Resolution	Number of Simulated Dwelling(s), hh(s)	Validation	Model's Scale	Country
a16	Bottom-up: Statistical	stochastic load model	NHPP model	Hourly	Brazilian homes	Compared with the measured data	Household level	Brazil
a17	Bottom-up: Statistical	ANN	ANN-based forecasting model	Daily and hourly	99 Households/1 random household	Performance metrics: MAPE, SDE and serial correlation	Household level	Portugal
a18	Bottom-up: Statistical	Multivariate Autoregressive(M-AR) model and CST-LF	outdoor temperature values, humidity and the social activities specific to some time periods	Hourly	173 houses	Compared with the measured data and MAE, RMSE, NRMSE	Household level	United States
a19	Bottom-up: Statistical	Mathematical model for load generation	Type of house, electrical appliance	Hourly	323 houses	Compared with the measured data	Local level	Singapore
a20	Bottom-up: Statistical	Stochastic model	Appliance usage, people behaviour, thermodynamical aspects	One-minute	41 houses	Compared with real data	household and neighbourhood level	Sweden
a21	Bottom-up: Engineering	A developed partial differential equation (PDE) physics-based model	Thermal behaviour	Hourly	EWH data	compared to the field measurement data	Appliance level	United States
a22	Bottom-up: Engineering	Measurement devices	Appliance usage	One-second, One-minute	2 houses	No validation	Appliance level	United States
a23	Bottom-up: Statistical	The electric load mathematical model	The building loads, appliances usage	Hourly	1 house	Compared with EnergyPlus, the validated building simulation software	Household	Not specified

ID	Approach	Method	LP's/Model's Input	Time Resolution	Number of Simulated Dwelling(s), hh(s)	Validation	Model's Scale	Country
a24	Bottom-up: Statistical	fuzzy logic systems	Appliance usage, lightings	Hourly	1 house	Compared with other projects	Appliance level	Spain
a25	Bottom-up: Engineering	Use existing home energy management systems (HEMS)	Appliance usage	Daily	40 single family homes	Compared with the measured data	Appliance level	United States
a26	Bottom-up: Statistical	Stochastic model	Dwelling characterisation and application usage	Hourly	Na	Compared with other data: Spanish and European	Neighbourhood and household level	Spain
a27	Bottom-up: Statistical	Stochastic model	Active occupancy, appliance use	Hourly	320 households	compared with the occupancy profiles directly obtained from TUS data	Neighbourhood and household level	Spain
a28	Bottom-up: Statistical	Probabilistic model	Household profile, Appliance usage	Hourly	Not mentioned	(na) Demonstrated only of two case examples	Household	Not specified
a29	Bottom-up: Engineering	Non-Intrusive Load Monitoring (NILM)	Appliance usage	One-minute	Not mentioned	Compared with other experiment	Appliance level	Korea
a30	Bottom-up: Statistical	statistical or probabilistic: Markov chains processes	Occupant behaviour, weather condition	one-minute	800 households: 80 connections point = 10 hh	Compared with measured data	Household	Germany
a31	Bottom-up: Statistical	Statistical analysis	Occupancy profiles, appliance usage and thermodynamical aspects	Hourly	2 buildings	Compared with the Italian standard	household and neighbourhood level	Italy

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