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A Comprehensive Review of Residential Electricity Load Profile Models

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ABSTRACT A third of the final electricity in the EU is consumed by households. The increased usage of multiple electrical devices, electromobility, self-generation and consumption of electricity as well as work-from-home will fundamentally change the residential electricity load profile, so a deep understanding of the current state of residential electricity load profile modelling is necessary. The objective of this paper is to perform a literature review, evaluate the current state of the residential electricity load profile modelling, categorise the models, propose future research directions and applications, identify the challenges the researchers face when building these models and offer possible solutions. Thirty two residential electricity load profile models are identified and a new definition of the residential electricity load profile model is proposed. A new categorisation system based on the identification of the main features of these thirty two studies is introduced. Future research directions and applications are presented and the most important challenges that modellers face when attempting to build such models are identified and discussed. The most important challenge identified is the privacy concerns of the participants or potential participants. These concerns are at least partially responsible for the existence of the rest of the challenges. The creation and implementation of an anonymisation algorithm, before any human has access to any measured datasets, the implementation of a crowd sourcing approach which addresses the privacy concerns of the citizens and increased funding for the installation of privacy-proof smart-meters by the public and measurement campaigns are identified as possible solutions to the challenges faced by modellers.

INDEX TERMS Load modeling, demand forecasting, load management, smart homes, power demand, electricity consumption, residential electricity load profile model, demand-side management, household electricity load profile model, residential power demand.

I. INTRODUCTION

Modern societies use an ever increasing number of electric and electronic devices. At present, on average 19 % of a European nation's energy is consumed by household electrical devices such as smartphones, televisions, gaming consoles, kitchen appliances, interior smart heating, water heaters, smart appliances, virtual assistants, interior and exterior lighting, and electric cars [19].

For decades research has heavily focused on power grid load models. Such models include the total electricity demand loads in the grid, from factories to small businesses, street lighting, the electricity demand of electric buses, trams, trains, household electricity demand and any and all other sources of electricity demand in the grid. During all this time it has been widely believed that residential load demand (which focuses specifically on the electricity demand load of households) does not vary strongly from house to house regardless of the socio-economic circumstances of its inhabitants and the number of people living in it, whether it be a single family house, an apartment or an apartment building. Therefore, it could be easily predicted on a quarter-hourly basis. As a result, the electricity providers of each country are using a single electricity consumption profile (known as the standard load profile (SLP)) to forecast the electricity consumption profile of all the houses of the country [12]. Some countries even use the same residential standard load profile, e.g., Germany and Austria. The German standard load profile (H0 SLP), which was created by the German Federal Association of Energy and Water Management (Bundesverband der Energie- und Wasserwirtschaft e. V. (BDEW)) [12] is also used by the Austrian government regulator for electricity

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and natural gas markets (Energie-Control Austria für die Regulierung der Elektrizitäts- und Erdgaswirtschaft also know as E-Control [18]).

Recent measurements of residential load profiles using smart meters have shown that the residential load profile is neither easily predictable nor easy to model because individuals use electricity-powered devices at different times depending on their own individual schedules and lifestyles [48]. As Stokes *et al.* [48] reported "Whilst some elements of the demand (e.g. lighting during hours of darkness) are less diversified, others (e.g. use of kettles or hobs) can be very different from one consumer to another". This household individuality means not only the presence of jumps and troughs in the electricity consumption profile when a device is turned On/Off, but also the presence of high levels of temporal variability, especially for sampling rates higher than 15 minutes (which is the sampling rate of the H0 SLP [12]).

In the next decades, the residential load profile will change radically due to the rise of electro-mobility, the surge in ownership of electricity-power devices, the projected increase of the Earth's population to 10 billion humans, the rise of new social conditions (e.g. working from home) as well as the self-generation and consumption of electricity through the installation of photovoltaic panels on the external surfaces of houses. In order to be able to study, understand and forecast these changes, a solid understanding of the residential load profile and its modelling in its present state is needed. At the time of writing of this paper, there is only one review of residential electricity load profile models, written by Grand Jean *et al.* [23], but it only focused on bottom-up residential electricity load profile models. A review of all the existing residential load profile models is, hence, necessary.

This review paper aims to perform a literature review of all the existing residential load profile models, assess the state of the art, and answer the following questions:

1) What is the definition of the residential electricity load profile model?
2) How can the existing residential electricity load profile models be categorised?
3) What approaches have been used to model the residential electricity load profile?
4) What are the parameters commonly used in residential load profile modelling?
5) What are the future research directions and applications of residential electricity load profile models?
6) What challenges do the researchers who build such models face?
7) How can these challenges be overcome?

This paper will be of especially high interest to electrical grid, demand side management and residential demand researchers and engineers alike.

In Section II, a definition of the residential load profile model is suggested and the methodology used in this review is described. In Section III, the approaches presently used to model the residential load profile are presented and a new model categorisation system is suggested. In Section IV, the parameter identification methods commonly used in load profile modelling as well as the major residential electricity loads and their categorisation are presented. In Section V, future research directions and future applications of residential electricity load profile models are presented. In Section VI, the challenges that researchers face are presented and in Section VII ways to address these challenges are suggested. Lastly, the conclusions are presented in Section VIII.

II. DEFINITIONS AND METHODOLOGY

A. DEFINITION OF A RESIDENTIAL LOAD PROFILE MODEL

Before beginning the review, the term "residential load profile model" must be defined. The first step is to define the individual components of the term:

Residential: private residences, with no commercial usage, occupied by one or more persons either full-time or part time during a calendar year.

Load: the electricity that all the electricity-powered devices in the household consume in unit time.

Profile: a graph representing the significant features of the electricity load over time.

Model: "a formal system that represents the combined processes" [29] of electricity consumption by all the electricity powered devices in a private residence/number of residences.

Because this review focuses on models that can reproduce the residential load profile in a calendar day, demand-side management electricity consumption models were generally excluded unless they could reproduce the residential load profile of a household for a minimum of one calendar day. When the above definitions and limitations are combined together, they produce the following definition of the residential load profile model:

The residential load profile model is 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. The residence/s must be occupied by at least one person for at least part of the calendar year. The input data are parameters that characterise the household, its occupants and their behaviour.

B. REVIEW METHODOLOGY

A literature survey revealed that different sectors, disciplines and applications use different terms to refer to models that fit the above definition. In order to collect all the relevant studies on the subject, the following list of different keyword combinations were used: load profile modelling, load profile generation, end-use electricity consumption model, home electricity consumption model, residential power demand model, home power demand model, household electricity load profile model, residential load profile model, domestic electricity load profile model, end-use electricity load profile model, NILM electricity consumption model, NILM load profile model, NILM electricity

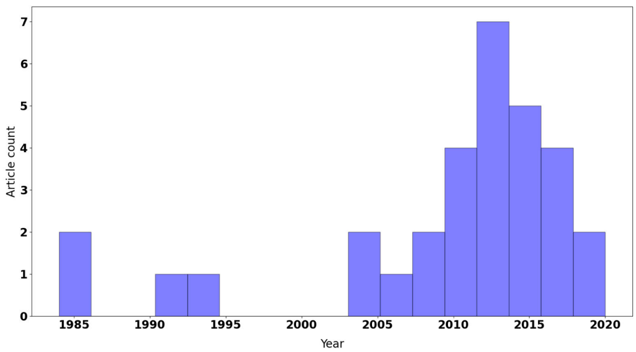

FIGURE 1. Distribution of publication dates of the collected papers. The majority of the models were published after 2002, with only four published between 1980 and 2002.

demand model, disaggregation load profile model, disaggregation electricity consumption model, disaggregation electricity demand model. It is worth noting that no online search engine or database exists that contains all the relevant publications. As a result, literature searches in both the ISI Web of Knowledge and Google Scholar were performed.

Both searches excluded all publications whose contents did not fit the above definition. The Google scholar search produced 25 relevant publications. The Web of Knowledge the search produced a total of 28 relevant publications. It is worth noting that the searches using the "end-use electricity load model", "end-use electrical load model", "end-use electricity load profile", "NILM electricity consumption model", "NILM load profile model", "NILM electricity demand model", "disaggregation load profile model","disaggregation electricity consumption model", "disaggregation electricity demand model" keyword combinations did not return any relevant results. By merging the two lists and eliminating any duplicates, the total number of relevant publications identified through the Google Scholar and Web Knowledge search was 32.

The identified studies span the last four decades, with the majority of them published after 2002 (the median year is 2009). The distribution of the publication dates can be seen in Figure 1. As can be seen, this review reports the state-of-the-art practices.

III. MODELLING APPROACHES

At present, residential load profile models are divided in two categories: bottop-up and top-down models. In this section, a new categorisation system is proposed based on the identification of the main features of the thirty two studies presented in the previous Section. These features are:

Method: This feature describes the methods used to build a residential load profile model. For example, if the electricity consumption of multiple devices in a household were used to calculate the electricity consumption of the household, then the model is assigned to the bottom-up model subgroup whereas if macro-economic parameters were used to calculate the electricity consumption of the household, then the model is assigned to the top-down subgroup.

Sampling rate: This feature describes the finest grain output that the model can generate. The output, rather than the input, was chosen because models can have multiple inputs with multiple sampling rates, but their outputs usually have a single sampling rate. This considerably simplifies the model comparison. So, a model that uses quarter-hourly occupancy profiles as input to calculate the hourly electricity consumption of a household is classified as having an hourly sampling rate. However, if quarter-hourly occupancy profiles were used to calculate the quarter-hourly electricity consumption of a household, then the sampling rate would be classified as quarter-hourly.

Application: This feature describes the model's primary intended application. If the output of the model or the model itself was to be used in demand side management, then the model is assigned to the demand side management subcategory. However, if it was to be used for planning and control design of energy systems and distributions grids, then the model is assigned to the planning and control design of energy systems and distributions grids subcategory. Lastly, if a model's only goal was to model the electricity consumption of a single house or a group of houses, then it is assigned to the residential load profiles subcategory.

Statistical techniques: This feature describes the main statistical technique/s used to model the residential load profile. If the main statistical technique used in a model was the Markov Chain technique, then the model is assigned to the Markov chain subgroup. If, on the other hand, a Monte Carlo technique was used, then the model is assigned to the Monte Carlo subgroup.

These categories together with their subcategories are presented below.

A. BASED ON THE METHOD

The most commonly used categorisation is the one based on the method used to calculate the electricity consumption of the household. Under this categorisation scheme, the models have historically been divided into bottom-up and top-down models. Recently, models who share characteristics with both the bottom-up and the top-down subcategories have been built to support demand side management. These models cannot be placed in either category. Since the use of demand side management technologies is expected to increase, a new subcategory of "Hybrid models" should be introduced. The three categories, with their characteristics, their advantages, their disadvantages and the categorisation of each model are presented below.

1) BOTTOM-UP MODELS

Bottom-up residential load profile models "calculate the individual dwelling energy or electricity consumption and extrapolate these results over a target area or region" [49]. They are built by identifying the electricity consumption of each appliance in a household, the household occupant's behaviour patterns, their related use of appliances and then aggregating them together to produce the total household electricity consumption profile.

Depending on the intended usage of the model, its input data might also include the characteristics of the house (e.g. size, layout, building materials), the weather conditions and the heating/cooling characteristics of the house (when they are electricity based). They can generate very detailed, single household electricity load profiles which can be adjusted to include or exclude appliances, include different device usage patterns and include future technologies, such as new devices with demand side management capabilities. As a result, they can help identify the influence of individual households or technology contributions to the electricity consumption profile of a residential block and are imminently suited for simulations investigating the effects of different technologies, policy decisions or energy optimisation techniques. They can also be used for demand forecasting at the utilities level. From there, they can then extrapolate the household electricity consumption profile to the village/city/federal state/country level. By calculating the energy consumption of groups of houses and then aggregating them, they can then create a SLP [41]. This extrapolation is usually accomplished by assigning a weight on each house or groups of houses. The weight assigned depends on the number of houses it represents [41].

The common procedure to develop a bottom-up model is the following:

1) **Step 1:** Determine the micro-variables of the model, i.e., the end-use equipment present in the household/s (e.g., the electrical appliances, the electrical space heating and the electrical water heating)
2) **Step 2:** Determine the human activity patterns for using these appliances from existing data (e.g., time use data)
3) **Step 3:** Generate the individual load profiles of each appliance of the household together with space and water heating for a period of time ranging from one day to several years
4) **Step 4:** Aggregate these individual load profiles from a single or multiple households for a period of time ranging from one day to several years
5) **Step 5:** Validate the model by comparing the simulation results with measured data

Bottom-up models have three main advantages: (a) they do not require the existence of historical electricity consumption data to determine the electricity consumption of the residential sector, (b) they are very well suited for studying the effects of different technologies, policy decisions or energy optimisation techniques on the household load profile, (c) they provide very detailed results. Their main disadvantages are: (a) they are very computationally heavy, as the high level of details introduce high levels of complexity in the models and (b) they have very high input data requirements such as active occupancy patterns, the equipment used in the households and information about the different time-uses of electricity consumers. Twenty one papers with sampling rates spanning from 1 hour to 1 second belong in this category and can be seen in Table 1.

2) TOP-DOWN MODELS

Top-down residential load profile models, on the other hand, "use the total energy or electricity consumption estimates to assign them to the characteristics of the building stock" [49]. They use macro-variables (data collected at an aggregate level) and/or stochastic predictors to predict the household energy consumption profile and use them to derive relationships between them and the electricity consumption. The most used macro-variables are the total residential sector electricity consumption, the structural characteristics of the dwellings, the number, age, sex, race/ethnicity, income, level of education and family type of occupants and their behaviour, as well as historical energy consumption data, weather conditions and macro-economic indicators. Household age (the ages of the household residents) is often used as a proxy for the amount of time people spend indoors and thereby the opportunity to consume energy. The stochastic predictors are based on time series analysis, such as auto-regressive moving average methods. According to Paatero *et al.* [52], they are more suitable for demand forecasting at the utility level because the end-use consumption of individual households is not usually distinguishable at the utility level. As a result, they are not as computationally intensive as bottom-up models.

The common procedure to develop a top-down model is the following:

1) **Step 1:** Find historical electricity datasets that have the proper sampling rates for the model
2) **Step 2:** Determine the macro-variables needed for the model (e.g., historical yearly electricity consumption, characteristics of the residents, historical weather data etc.)
3) **Step 3:** Categorise different combinations of macro-variables (e.g., a single family building where a couple with 2 school age children of ethnicity A who earn B euros per year in the North of Germany live versus an apartment where a single female of ethnicity C who earns D euros per year in the South of Germany live.)
4) **Step 4:** Perform time series analysis on the historical data to determine the stochastic predictors to be used in the model (if any)
5) **Step 5:** Combine the stochastic predictors with the macro-variable categories to generate the load profile of the house/s for a period of time ranging from one day to several years
6) **Step 6:** Validate the model by comparing the simulation results with measured data

The two main advantages of top-down models compared to bottom-up models are that (a) they do not require information about individual electric appliances and (b) they have a low level of complexity because they do not require the modelling of the usage of every single appliance in the household and are, therefore, not as computationally heavy as bottom-up models. Their main disadvantages are that (a) they require the existence of historical data of residential electricity consumption profiles of households to determine the energy consumption of the residential sector and (b) have large computational time steps (usually between 15 minutes and 1 hour [17]). This results in the loss of information as only certain statistical criteria can be fulfilled [13]. Top-down models are imminently suited for simulations studying the demand-response, the transformer and storage sizing, as well as the distribution networks. Seven papers with sampling rates between 1 hour and 30 minutes belong to this category and can be seen in Table 1. As can be seen, there are far fewer top-down models than there are bottom-up ones.

3) HYBRID MODELS

Hybrid models are a fairly recent addition to residential load profile models (with the exception of [10]). As the name implies, combine methods and elements used in both bottom-up and top-down models. Bottom-up elements include, but are not limited to, occupancy models, electrical appliance usage, consumption load profiles, lighting usage, hot water demand and natural ventilation. Top-down elements include, but are not limited to, building archetypes, which are representative of a group of buildings and their electricity consumption profiles.

The common procedure to develop a Hybrid model is the following:

1) **Step 1:** Determine which micro- and which macro-variables will be used in the model
2) **Step 2:** Use the bottom-up model procedure steps a) – c) for the micro-variables
3) **Step 3:** Use the top-down model procedure steps a) – d) for the macro-variables
4) **Step 4:** Combine the micro- and macro-variables to generate load profiles for a single or multiple households for a period of time ranging from one day to several years
5) **Step 5:** Validate the model by comparing the simulation results with measured data

Most hybrid models were created to support demand side management efforts (more specifically, demand forecasting using smart meters). As a result, each model incorporates a different set of techniques and input parameters depending on the problem they were meant to solve. Therefore, the characteristics they share with bottom-up and top-down models strongly vary from model to model. It is not possible to create a list of advantages and disadvantages because each hybrid model combines different elements of bottom-up and top-down down models. Four papers with a sampling rate ranging from 1 hour to 2 seconds belong to this category (see Table 1). As can be seen, hybrid models are the least numerous but this will most likely change as demand side management and smart meters become more widely used.

B. BASED ON THE SAMPLING RATE

The literature research showed that the models can be divided into three broad categories: low resolution models, middle resolution models and high resolution models.

Low resolution models (see Table 1) are models with a sampling rate less than fifteen minutes. All but one such models were created before 2015 and could be divided into two broad categories. Those belonging to the first category aim to model the end-use electricity of a region, i.e., neighbourhoods, districts, cities or provinces. Depending on the model the region could be composed of hundreds ([10], [20], [47]) to hundred of thousands of households ([14], [32], [45], [52], [57]). Those belonging to the second category aim to model the electricity load profile of different types of houses ([3], [37], [42], [53], [54], [56]) or study the impact of different energy prices on the residential load profile [22] and, hence, only modelled single houses.

Middle resolution models (see Table 1) are models that have a sampling rate between fifteen minutes and one minute. They are by far the least numerous and, at the time of writing of this review, only four such models exist (see Table 1). All of these models were created after 2000. In general, they simulated the residential load profiles of single houses that could then be studied individually.

High resolution models are models with a sampling rate of one minute or more. All were published after 2010, with the notable exception of [48] which was published in 2005. Such models are much more likely to have been built using not only measurements of the main power supply but also of household electrical devices, who have internal time scales of milliseconds ([11], [28]). Of the high resolution models, only one has a sampling rate of two seconds [88] and none exist with a sampling rate of the order of milliseconds. It is worth noting that, when most publications refer to high-resolution residential load models, they are actually referring to middle resolution models because no models with a sampling rate of the order of seconds existed when they were published.

All residential load profiles are dynamic models in the sense that the generated electricity consumption depends on the time of the day, the number of household residents present at any given time and their occupancy and appliance usage patterns. However, models with low sampling rates (of the order of hours to 15 minutes) display far fewer changes of state than models with high sampling rates (1 minute to Hz). The reason for this is that most low sampling rate models are attempting to replicate H0 SLP-like profiles produced in different countries. The H0 SLP was created using $\approx 90\%$ hourly sampling rate data and $\approx 10\%$ quarterly hour sampling rate data [12], i.e., the hourly sampling rate data recorded one value every hour while the quarterly hour sampling rate data recorded one value every 15 minutes. The hourly data were then upsampled to a sampling rate of 15 minutes. As a result, they completely miss the demand fluctuations present in the periods in between. Furthermore, the H0 SLP assumes that each week day has exactly the same load profile, while Saturday and Sunday each have a different profile. High temporal resolution profiles, on the other hand, do reflect the fluctuations generated by the turning on and off of appliances and are, therefore, much more dynamic than low sampling rate models (see [88]). It should also be noted that the mathematical properties of residential electricity loads depend on their spatial scales and the number of houses being considered. The larger the number of houses, the smaller the fluctuations would be, but they would still be present and clearly visible (see [88]). A more detailed discussion on how the number of houses, the sampling rate of a model and the data that were used to create it affect the mathematical properties of a residential load model can be found in [88].

C. BASED ON THE APPLICATION

The model itself or its output can have several primary intended applications, usually more than one at the same time. As with the categorisation based on the sampling rate, there is no official classification. However, the models can be divided into four broad categories: (a) demand side management (DSM), (b) planning, control and design of energy systems, distributions grids and local energy efficiency strategies (PCD) and (c) residential load profiles (RLP).

1) DEMAND SIDE MANAGEMENT

Models whose primary intended application is to be used in demand side management systems are grouped in the demand side management subcategory. Such models are concerned with how the electricity consumption of households can be reduced/altered through the implementation of new technologies or shifted to times of the day with historically low electricity demand and/or when the electricity prices are low. This can be achieved through the implementation of new technologies in household appliances such as energy efficient fridges or room heaters that can be pre-programmed to switch on at specific times. Some of these devices can also use algorithms that can switch appliances On/Off on demand, or when certain conditions are met or schedule their usage in advance for a certain time period of the day. Examples of such appliances are washing machines that are switched on when the price of electricity drops below a certain threshold, devices that switch On/Off when the outdoor or indoor temperature reaches a certain value or washing machines and robotic vacuum cleaners which can be controlled remotely. Eighteen such models were identified (see Table 1).

2) PLANNING, CONTROL AND DESIGN OF ENERGY SYSTEMS, DISTRIBUTIONS GRIDS AND LOCAL ENERGY EFFICIENCY STRATEGIES

Models whose primary intended application is the planning, control and design of energy systems, distributions grids and local energy efficiency strategies (PCD) fall into this subcategory. Such studies aim to help electricity grid planners build electricity grids which minimise electricity consumption using different technologies including demand side management. Nine such models were identified (see Table 1).

3) RESIDENTIAL LOAD PROFILES

Models whose sole declared application was the generation of residential electricity load profiles (REL) were placed in this last subgroup. Nineteen such models were identified (see Table 1).

D. BASED ON THE STATISTICAL METHODS

Lastly, the models can be grouped based on the statistical methods used to model the residential load profile.

1) MARKOV CHAIN MODELS

Fourteen of the models surveyed used Markov chains (MChain) to simulate the switching On/Off of devices (see Table 1), with the majority of them assuming that the activation/deactivation of a single device is independent from the activation/deactivation of any other devices present in the household. This assumption is often false, e.g., if a house possesses both a washing machine and a dryer. In that case, the usage on the washing machine will be followed by the usage of the dryer after the washing machine has finished [19]. Of the fourteen models in this category only two ([19], [46]) considered the paired usage of devices. Virtually all the models used a combination of the usage patterns of residents and the load profiles of the devices to model the electricity load of the household. In general, such models defined a starting state which then transitioned to the next states. The state the system transitioned to depended on the transitioning probability. Each model used a different method to calculate it. Some used transitional probability matrices. Others used a generated uniformly-distributed pseudo-random number which when compared to the cumulative distribution of the state transition determined which transition took place. Yet in others the probability of transitioning from an On to an Off state was a time-dependent parametrised binary function whose parameters were determined by a cumulative distribution function.

2) PROBABILISTIC MODELS

Twenty five models (see Table 1) used non-Markov, probabilistic statistics (PPM) to model the residential load profiles of single houses. These models used general statistical methods such as sums of Gaussians, probability distributions, cumulative probability functions or conditional demand analysis to model the load profiles of individual appliances and whole households. These models display a wide range of complexity. They have been used to determine whether devices are On or Off and, in the case of devices with uncertain usage periods, to determine for how long a device was used. Moreover, they have been used to develop the occupancy profiles of the houses. Only one model used parameter fitting to extract the optimal values for their model parameters [20] while the rest assigned probabilities by criteria that limited their average values to within tolerance bands around the values indicated by national statistics or measured data.

3) MONTE CARLO MODELS

Five models combined a PPM and/or MChain approach with the usage of Monte Carlo methods (MCarlo) (see Table 1). These method were used to extract the probability profile of a process [14] or to determine whether devices were used and, in the case of devices with uncertain usage periods, to determine how long they were used for [47]. Neue *et al.* [41] used these methods to develop activity-specific profiles for occupancy, disaggregated appliance and indoor-lighting electricity usage. Muratori *et al.* [39] used these methods to create residential load profiles which connected the electricity demand with psychological and behavioural factors typical of the household occupants. Labeeuw *et al.* [32] used these methods to create a wide variety of residential customer profiles, where each profile represented a group of households with similar consumption patterns. Johnson *et al.* [27] used these methods to combine occupant behaviour and residential load models to simulate variations in electricity consumption based on the time of the day and day of the week. All models usually used measured residential load profile data and statistical methods such as clustering algorithms and goodness-of-fit to find the optimal values for their parameters.

In general, as can be seen in Table 1, each model uses whichever statistical method or combination of methods gives the best results for its intended purpose as well as the input datasets available to its authors. This review could not identify any clear preferences for the usage of one statistical method over another in any type of model. Actually, the use of the statistical methods appeared to be strongly influenced by the type of data available to the authors and, therefore, by how that data could be used to build a model that could create the residential load profile of a house or a group of houses.

However, because low sampling rate datasets (15 minutes - 1 hour) are deterministic in nature [37], they can be easily modelled using simpler methods such as sums of Gaussians, probability functions, cumulative probability functions or conditional demand analysis. At high sampling rates (1 minute - several Hz), however, the stochastic nature of the residential electricity consumption becomes evident. This stochastic nature is due to the randomness of the switching On/Off of devices by the residents of each house [88]. As a result, stochastic methods usually need to be combined with deterministic methods to accurately model residential load datasets measured at high sampling rates. Consequently, Markov processes and Monte Carlo techniques are used often but not exclusively (e.g., the usage of only probability distributions in [17] and [19] shows). A summarised version of the suggested categories and their subcategories are shown in Table 2.

In conclusion, residential load models can be categorised in several different ways depending on their structure, their sampling rate, their intended application and their statistical techniques. Until now, however, authors focused only on the categorisation based on their structure and ignored models which combined characteristics of both bottom-up and top down models.

IV. PARAMETER IDENTIFICATION

In general, the parameters chosen as model input depend strongly on the type of the model. Micro-parameters, such as appliance load and time-use/user activity information, are more common in bottom-up and hybrid models. Macro-parameters, such as building stock, demographics (number, age, sex, race/ethnicity of household occupants), socio-economic data (income, level of education and family type of occupants) and lifestyle habits (time people spend indoors, types of household entertainment, amount of home cooking etc.), are more common in top-down and hybrid models.

A. MICRO-VARIABLE CATEGORIES AND THEIR PARAMETER IDENTIFICATION

Models whose input is the load profile of individual appliances (while they are in use and their yearly consumption) obtain the values of their parameters from (a) directly from the manufacturers ([24], [39], [42], [47], [52]), (b) from measurements performed under controlled conditions (e.g., in laboratories [53]), or (c) from state/country authorities or universities organised and funded by states/countries who then make the anonymised data available to researchers ([7], [14], [19], [22], [32], [35], [45]–[47], [52]–[54]). More rarely, they are measured directly through intrusive appliance monitoring (i.e., through metering devices attached to the household appliances of the participants during the measurement campaigns) ([10], [27], [42], [46], [55]). The sources of the values used in [5], [17], [24], [36], and [56] are unclear. With the advent of non-intrusive load modelling (NILM) and disaggregation techniques, it is now possible to extract the load profiles of individual appliances from the metered load profiles of single houses as long as the data is accessible.

According to Picon *et al.* [90], there are four categories of micro-variables used in bottom-up residential load profiles. In the first category belong electrical appliances that can only be switched on or off, e.g., ovens and hot water kettles (see Figure 2a,b). In the second category belong appliances whose electricity consumption is adjustable such as stoves, irons, fans and hair dryers (see Figure 2c,d). In the third category belong appliances during whose operation different consumption events happen, such as washing machines. They have different washing programs (with or no pre-wash, with hot, warm and cold water programs, for woollen, synthetic or mixed fibre clothes etc.) and each program is characterised by different processes (washing, rinsing and spinning cycles). This results in variable electricity consumption during their operation (see Figure 3). Other devices that also belong to the third category are refrigerators, PCs, laser printers and televisions (see Figure 4). In the last category belong appliances which are always in use and have one (constant) consumption rate. Any appliance with a stand-by mode (while it remains on stand-by mode) belongs in this category. Such appliances are PC monitors (when not turned off or being used), microwaves with digital clocks (when not used) and modems. These appliances form the base load of

TABLE 1. Model categorisation table. The models are sorted according to the method used to calculate the electricity consumption of the household and their year of publication. The table also provides information about the sampling rate of each model, their intended application and the statistical technique/s used.

Authors	Year	Sampling Rate	Application	Modelling Techniques
Bottom-up modes				
Train et al. [57]	1984	1 hour	RLP	PPM
Walker et al. [56]	1985	15 minutes	PCD, RLP	PPM, MChain
Yao et al. [54]	2005	1 hour	DSM, RLP	PPM
Melody Stokes [48]	2005	1 minute	PCD, RLP	PPM
Paatero et al. [52]	2006	1 hour	DSM, PCD, RLP	MChain, PPM
Armstrong et al. [7]	2009	5 minutes	DSM	MChain, PPM
Richardson et al. [46]	2010	1 minute	RLP	PPM, MChain
Dickert et al. [17]	2010	30 s	DSM, PCD	PPM
Ren et al. [45]	2012	1 hour	DSM, PCD, RLP	PPM
Gruber et al. [24]	2012	1 minute	DSM	MChain, PPM
Shao et al. [47]	2013	1 hour	DSM	PPM, MCarlo
Muratori et al. [39]	2013	10 minutes	RLP	MChain, MCarlo, PPM
Bajada et al. [8]	2013	1 minute	DSM	MChain
Ortiz et al. [42]	2014	1 hour	RLP	PPM
Alzate et al. [3]	2014	15 minutes	DSM	MChain
Collin et al. [16]	2014	10 minutes	DSM, PCD	MChain
Fischer et al. [19]	2015	10 s	DSM, REL	PPM
Gao et al. [55]	2016	8.5 minutes	DSM	PPM
Marszal-Pomianowska et al. [35]	2016	1 minute	DSM, PCD	PPM
McKenna et al. [5], [36]	2016	1 minute	RLP, DMS,	PPM
Gottwalt et al. [22]	2018	1 hour	DMS	MChain, PPM
Top-down modes				
Capasso et al. [14]	1994	15 minutes	DSM, RLP	MCarlo, PPM
Widen et al. [53]	2009	1 hour	RLP	PPM
McLoughlin et al. [37]	2010	30 minutes	RLP	MChain
Bucher et al. [13]	2012	1 minute	RLP	PPM

TABLE 1. *(Continued.)* **Model categorisation table. The models are sorted according to the method used to calculate the electricity consumption of the household and their year of publication. The table also provides information about the sampling rate of each model, their intended application and the statistical technique/s used.**

Labeeuw et al. [32]	2013	1 hour	RLP	MChain, MCarlo, PPM
Ge et al. [20]	2016	1 hour	PCD	PPM
Anvari et al. [87]	2020	2 seconds	DSM, RLP	PPM
Hybrid modes				
Bartels et al. [10]	1992	1 hour	DSM	NMCPS
Ardakanian et al. [6]	2011	1 minute	PCD, RLP	MChain
Johnson et al. [27]	2014	1 s	RLP	MChain, PPM
Neue et al. [41]	2016	1 minute	DSM	MChain, MCarlo

TABLE 2. Model categorisation summary. Categorisation of the reviewed models based on their main features. The subcategories of each category are also presented.

Categories according to the model's main features	Subcategories
Methods used in the model	1) Bottom-up models 2) Top-down models 3) Hybrid models
Sampling rate	1) Low resolution (hours - 15 minutes) 2) Middle resolution (15 minutes - 1 minute) 3) High resolution models (1 minute - Hz)
Intended application	1) Demand side management 2) Planning, control and design of energy systems, distributions grids and local energy efficiency strategies 3) Residential load profiles
Statistical techniques	1) Markov chain techniques 2) Probabilistic techniques 3) Monte Carlo techniques

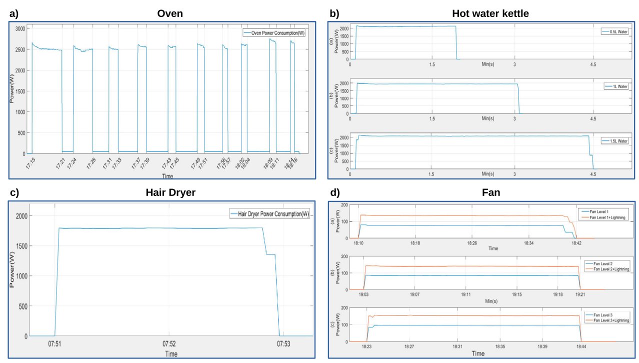

FIGURE 2. Appliance category 1 & 2. a) oven and b) hot water kettle, are Category 1 appliances which can be turned on and off. The small fluctuations can probably be attributed to sensor noise. c) hair dryer and d) fan are Category 2 appliances. The different electricity consumption modes are clearly visible in the form of steps in the case of the hair dryer. In the case of the fan the different electricity consumption modes are visible in the form of different colour lines and the presence of steps. The loads were measured in November 2016. The plots were originally published by Gao *et al.* [89] and edited to allow their presentation in a single figure.

the load profile [91] and, because they are always On, cannot be identified using disaggregation or NILM analysis. The effects of various devices on the residential load profile as well as the base load (the constant consumption of ≈ 0.5 kW) can be seen in Figure 5. A more in depth analysis on the classification of household appliances can be found in [24].

As electric vehicles (e.g. cars, scooters, bicycles) are gaining in popularity, manufacturers are starting to produce e-vehicle load profiles. Such manufacturer profiles have low sampling rates (15 - 30 minutes). The e-vehicle load profile depends on several factors such as the type of electric vehicle (e.g. bike, scooter or car), the size of its battery, its nominal charging power, the typical daily driven distance and the daily energy requirement, the typical charging times (in the morning or in the evening or over the course of the day). E-vehicles should be placed in Category 1 because they appear to charge at a constant rate of, e.g., 160 W and stop charging as soon as the battery is full or the car is disconnected from the plug. An example of such a load profile can be seen in Figure 6.

B. MACRO-VARIABLE CATEGORIES AND THEIR PARAMETER IDENTIFICATION

Models whose input was the active power consumption of a single or multiple houses obtained the values of their parameters directly from measurements collected by metering devices attached to the houses main electricity power line

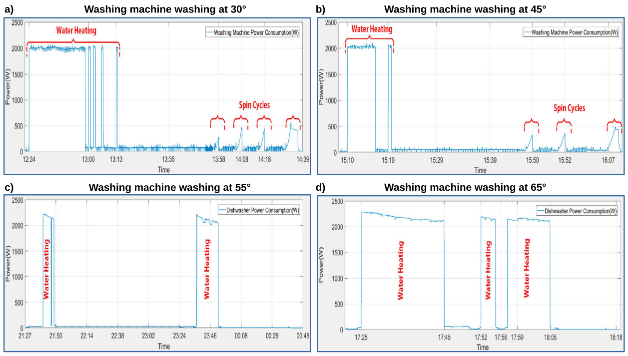

FIGURE 3. **Appliance category 3: Washing machine. The electricity consumption loads of a washing machine operating at a) 30 degrees, b) 45 degrees, c) 55 degrees and d) 65 degrees. The loads were measured in November 2016. The plots were originally published by Gao *et al.* [89] and edited to allow their presentation in a single figure.**

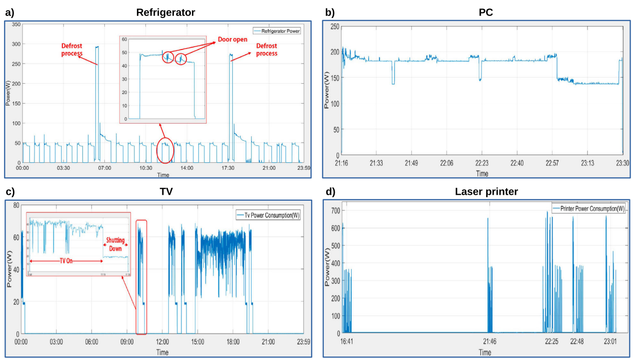

FIGURE 4. **Appliance Category 3. The electricity consumption loads of a) a refrigerator, b) a PC c) a TV and d) a laser printer. The variation in the electricity consumption of the devices is clearly visible in the form of abrupt jumps in the electricity consumption. Specific changes in state that result in the fluctuation of electricity consumption are marked for the refrigerator and the TV. The loads were measured in November 2016. The plots were originally published by Gao *et al.* [89] and edited to allow their presentation in a single figure.**

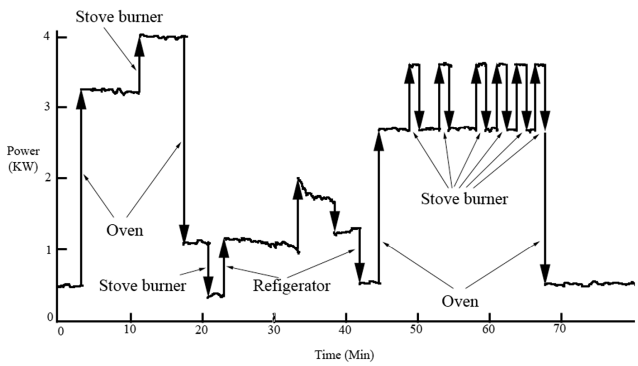

FIGURE 5. **Appliance influence on the residential electricity load profile. The electricity consumption load of a household with the various appliance loads and how they alter it are indicated. The noise visible can be attributed to sensor noise. The plot was originally published by Tuomisto [90].**

([6], [10], [20], [37], [46], [48], [88]) or were generated from older bottom-up models ([13], [41]).

Models whose input was a) time use data, b) user activity information regarding the length of usage of various appliances in households, c) demographic data (number, age, sex,

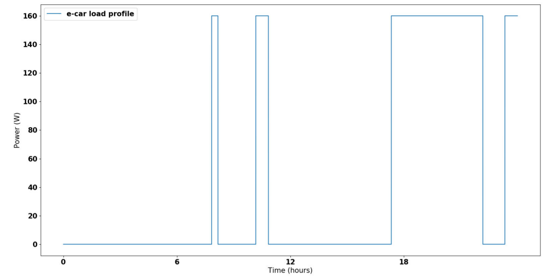

FIGURE 6. **Electric-car charging profile. The plot shows the charging profile of a an electric car. In this Figure the car is plugged in and charging 4 times over the course of 24 hours. Each time the car is connected to the plug and starts charging, the electricity consumption jumps from 0 to 160 W. The dataset used to create this plot was published by Muratori in 2018 [26].**

race/ethnicity of household occupants), d) socio-economic data (income, level of education and family type of occupants) or e) lifestyle habits usually obtained the values of their parameters from time usage diaries filled by participants of past measurement surveys ([3], [8], [14], [16], [19], [22], [27], [35], [39], [41], [42], [46], [53], [57]). Usually, these measurement campaigns were organised and funded by states/countries who then made the anonymised data available to researchers. On rare occasions, the data were collected by surveys conducted by the authors themselves [42]. Infrequently, models used usage profiles or normalised usage profiles found in older papers ([7], [41], [45], [54]).

Lastly, models whose input was residential building stock information (to determine the number of single houses, detached houses, semi-detached houses and blocks of flats) usually derived the values of their parameters from census surveys organised and funded by states/countries who then made the anonymised data available to researchers ([41], [48]). The geometrical characteristics, construction types and materials, appliance infiltration levels, heating system types and controls were usually determined from the building regulations for, both, new and existing buildings in the relevant countries ([41], [48]). The number of rooms, layout and floor plans were usually determined from representative dwellings defined in older studies ([41], [48]). On very rare cases, this information was also collected as part of measurement campaigns [55].

V. FUTURE RESEARCH DIRECTIONS AND APPLICATIONS

With the increasing number of renewable electricity feed-in, the ever increasing number of electricity-powered devices used in households (including vehicles) and the emergence of and integration into the electricity grid of mini- and micro-grids ([77], [78]) (which can be autonomous or semi-autonomous or fully connected to the grid), three main future research directions and applications for the residential electricity load models can be foreseen: a) Smart Homes, b) Mini-Grids, Micro-Grids and Smart Cities and c) investigating the effects of new appliances, new building technologies and new regulations on the residential load profile.

a) In **Smart Homes**, bottom-up or hybrid residential electricity load profile models could investigate and eventually be used for demand side management and load shifting. Such models would help households with installed photovoltaic/micro-wind electricity generation capabilities and battery storage to remain energy neutral by forecasting and load shifting the electricity demand to balance it with the generation. For houses who cannot generate their own electricity, they would allow them to reduce their electricity bills through load shifting or reduce their electricity consumption by highlighting devices that consume high amounts of electricity. These models would need to use live feed-in or historical data from smart devices/plugs and (if installed) renewable electricity generation sources.

b) In **Mini-Grids, Micro-Grids and Smart Cities**, top-down/hybrid residential electricity load profile models could be used to investigate how could i) load shifting or ii) demand forecasting of the small groups of houses, neighbourhoods or small villages belonging to these mini- and micro-grids help grid controllers maintain the stability of these grids. If future Smart Cities are composed of clusters of such grids, they could help maintain the stability of the entire city. Of course, in both cases (mini-, micro-grids and Smart Cities), they would need to be part of a larger grid model or a city-wide electricity grid model, respectively.

In the case of load shifting, the balancing would take place through active load shifting of the demand of each house (this would require access to the live feed-in of each house which would then be used as input for the model and would allow the controllers to control at least the major devices in each house). It will, therefore, be critical that the residents of each household actively opt-in to the system. In the case of demand forecasting, residential electricity load profile models could be used to forecast the electricity demand of the group of houses in advance (using the historical feed-in of the smart meters installed in each house). The forecasting would allow them to deploy extra energy resources (e.g., electricity from battery storage or hydrogen fuels or to buy electricity from the grid) when the demand is forecasted to be higher than the generation. It would also make it possible to fine tune the model to best fit the needs and characteristics of each individual mini- or micro-grid. For example, a cluster of student houses and dorms will have different consumption characteristics and peak times (high consumption in the morning and night but low during the rest of the day) compared to a retirement community (moderate consumption over the day with peaks in the early morning, lunch and dinner times). Such models could help both researchers and engineers identify the best technologies that could be used to successfully balance the generation and consumption ([78], [79]), the best protection schemes [80] and the best control systems to ensure the stable and secure operation of such grids ([81]–[83]) by providing accurate group residential load profiles for the particular mini- and micro-grids in question.

c) Lastly, residential load models could be used (as has been done in the past) to study how the addition of new devices (e.g., smartphones, tables, smart watches, gaming consoles, smart devices, etc.), new vehicles (e-cars, e-scooter, etc.), new social conditions (e.g., working from home), new building technologies and new building standards (passive/zero energy houses) will affect the residential electricity load profile and create short (the next few minutes) and long term forecasts (the next several weeks). They could also help study and analyse the impact of smart houses on the residential load profile of the future and, hence, help create plans and strategies.

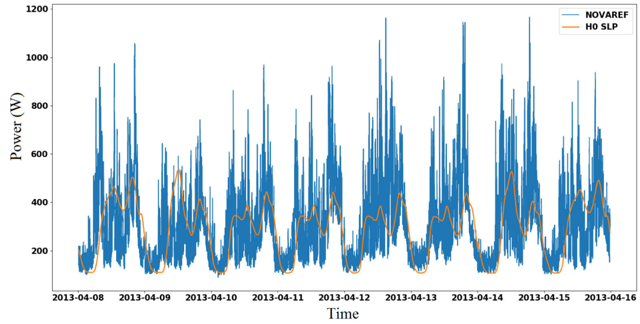

FIGURE 7. H0 SLP vs the measured residential load profile of a group of houses. Comparison of the H0 SLP used by German electricity providers vs the actual electricity consumption average of the 12 houses measured during the NOVAREF project [33] for the week between 08.04-15.04.

VI. MODELLING CHALLENGES

A. UNSUITABILITY OF THE BDEW H0 SLP

The publicly available H0 SLP [21] is not well suited to the creation of the residential electricity load profile models of the future because it assumes that every household follows the same electricity consumption patterns regardless of the number of the household occupants, their socio-economic status or the number and the type of electrical devices they use. The residential electricity load profile of a group of houses looks closer to the NOVAREF load profile visible in Figure 7 (which is the average of twelve houses recorded at a sampling rate of 2 seconds) measured during the NOVAREF project [33]. In reality, the residential load profile of a single household can vary strongly from house to house, as can be seen in Figure 8. Furthermore, the majority of the measurements that the BDEW used to create the H0 SLP were collected in the decades preceding 1990, with only a few measurements performed between 1995 and 1998. As a result, it completely ignores the effects that the increasing number of electrical devices introduced into the household since 1999 can have on the residential electricity load, especially on time-scales shorter than 15 minutes.

According to the BDEW report (which was written in 1999), a 10 – 20 % deviation between the predicted H0 SLP and the actual consumption was to be expected at any given time [12]. Due to the increased usage of multiple electronic devices (such as smartphones, smart speakers, electric heaters, gaming consoles, internal lighting etc.), electro-mobility, work-from-home, self-generation and

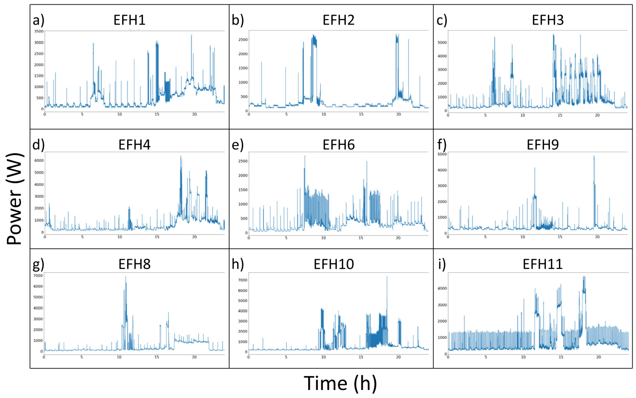

FIGURE 8. Daily electricity consumption measurements from 9 houses. The electricity consumption measurements of a selection of houses measured during the NOVAREF project for a single calendar day [33]. a) House 1, b) House 2, c) House 3, d) House 4, e) House 6, f) House 9, g) House 8, h) House 10, i) House 11. As can be seen, the residential electricity load of an individual house can vary greatly and usually looks very different from the H0 SLP.

individual consumption, the deviations between the expected and actual consumption are likely to be higher in 2020 than reported in the BDEW report and likely to increase even more in the next years or decades.

Another issue the H0 SLP does not address is the existence of "second" or "vacation" homes. The consumption characteristics of these houses can be radically different from those of the standard load profile, as they are characterised by either high consumption in the summer and low consumption in the winter or normal consumption during the week but zero consumption during the weekends (or vice-versa) [4].

Therefore, in order to create accurate models, researchers need to use residential electricity load profile datasets measured during measurement campaigns. Unfortunately, at the time of writing of this review, there are only 25 publicly available or available at request residential load profile datasets (see Table 3). The low number of residential load profile models in existence can be directly attributed to the limited accessibility to such datasets, which can itself be directly attributed to privacy concerns.

Residential electricity load profiles can also be created by combining the occupant behaviour datasets or models with publicly available datasets of short measurements obtained from various appliances. A table of six publicly available datasets of various devices can be seen in Table 4.

B. MODEL SOURCE CODE AVAILABILITY AND STRUCTURE

All the residential load profile models presented in this paper were created for and used in very specific projects. Each model tried to answer a very specific question or to address a very particular issue. Due to this and the fact that, for decades, it was believed that residential load profiles do not vary strongly from house to house, there has never been an industrial standard for residential electricity load profile models. The closest thing to an industrial standard in residential load modelling has been the H0 SLP-like datasets generated by each country's authorities or energy providers.

As a result, it was not common practice to make the source code of the models developed or the data used in the projects publicly available. Each of these modellers had to build their model from scratch. Had the source code been publicly available, they could have instead focused their efforts into adjusting the source code to fit their needs, increase the model's complexity or conduct more in-depth research rather than wasting their time and resources performing duplicate work.

Going forward, residential load models should facilitate the exchange of ideas and increase the collaboration within the community. In order to achieve these goals, future models should a) be made open source and b) be distributed under a Copyleft license [76] so that (i) proper credit is given and (ii) all software developed based on them are licensed under identical open-source terms. This will ensure the greatest possible impact by being universally accessible to all researchers. They should, furthermore, be c) properly documented so that the researchers have a full understanding of the source-code and d) be modular so that future users can add, remove and develop functionalities as needed.

C. PRIVACY CONCERNS

The number of residential load profile datasets in existence is higher than the twenty five publicly available ones presented in Table 3. Proof of this are the models presented in Section III, none of which was built using publicly available datasets ([88] did however make the datasets used to build it publicly available). Accessing these non-publicly available datasets can be challenging and often impossible as such datasets are usually collected in the course of measurement campaigns. These campaigns, and consequently the data collected, are controlled by strict privacy and confidentiality agreements which strongly restrict their sharing and/or usage in any project other than the one they were collected for. As a result, they cannot be shared with researchers unaffiliated with the institution/s they were collected by. Often, they cannot even be shared with researchers who belong to the same institution/s but are unaffiliated with the specific project the data were collected for.

This is very unfortunate as the data collected during such campaigns can be very valuable for model building, i.e., they might contain the total electricity consumption of a household/s and/or the electricity consumption of individual appliances and/or the electricity consumption of multiple appliances connected to a common plug. These quantities are usually measured in Watts per unit time (hour/fifteen minutes/minutes/seconds/milliseconds intervals depending on what is measured and the capabilities of the sensor used to measure them). The total electricity consumption of a household is measured by attaching a meter to the main power supply (Watts per hours/fifteen minutes/minutes/seconds intervals). The electricity consumption of individual appliances is measured by attaching smart meters to individual

TABLE 3. Publicly available datasets of residential electricity load profiles. This table presents all the publicly available residential electricity load profile datasets which contain measurements of a minimum of 24 hours. They are sorted by year of publication and include the sampling rate, the measurement period, the features of each dataset and the country where the data were measured. The features available are A1 = aggregate consumption of single household/s, A2 = electric car, A3 = individual circuits consumption, A4 = occupancy status, A5 = PV generation, A6 = micro-wind generation, A7 = individual appliances consumption, A8 = indoor temperature, A9 = outdoor temperature, A10 = building, room and appliance characteristics.

#	Acronym	Year	Sampling Rate	Submeters	Features	# Houses	Period	Country
1	SERL [71]	2020	daily & 30 minutes	-	A1	1770	2019-2020	UK
2	CRHLL [74]	2013	1 hour	10	A1, A3, A7	16	1 year	USA
3	HUE [75]	2019	1 hour	-	A1	28	1-2 years	Canada
4	Ausgrid Solar Home Electricity [68]	2010	30 minutes	-	A5	300	2011-2013	Australia
5	ISSDA Smart Meter Dataset [73]	2012	30 minutes	-	A1	4225	2009 - 2010	Ireland
6	LCLdToU [66]	2016	30 minutes	-	A1	5567	2013	UK
7	EDR Project [65]	2018	30 minutes	-	A1	16249	2007-2010	UK
9	H0 SLP [21], [12]	1999	15 minutes	Aggregated	A1	332	1970 - 1999	Germany
10	IZES [72]	2010	15 minutes	-	A1	497	2010	Germany
11	IEEE PES-ISS [62]	2015	15 - 5 minutes	-	A1, A2	10	8 - 30 days	USA, Brazil
12	Smart* (UMSM) [9]	2013	15 - 1 minutes	42	A1, A3, A4, A5, A6	400 and 7	2014-16	USA
13	IHEPCDS [25]	2012	1 minute	3	A1, A3	1	4 years	France
14	SustDataED [43]	2012	1 minute	24	A1, A7	50	2010-present	Portugal
15	MEULPv1 [69]	2012	1 minute	8	A1, A3	12	> 1 year	Canada
16	iAWE [11]	2013	1 minute	33	A1, A3, A7	1	73 days	India
17	AMPDs [34]	2013	1 minute	21	A1	1	2 years	Canada
18	MEULPv2 [70]	2017	1 minute	5 groups	A1, A2	12	1 year	Canada
19	REDD [31]	2011	10 & 3 s	24	A1, A7	6	several weeks	USA
21	REFIT [40]	2017	8 s	9	A1, A7	20	2 years	UK
22	Tracebase [63]	2012	2 s	158	A7	15	24 hours	Germany, Australia

TABLE 3. *(Continued.)* **Publicly available datasets of residential electricity load profiles. This table presents all the publicly available residential electricity load profile datasets which contain measurements of a minimum of 24 hours. They are sorted by year of publication and include the sampling rate, the measurement period, the features of each dataset and the country where the data were measured. The features available are A1 = aggregate consumption of single household/s, A2 = electric car, A3 = individual circuits consumption, A4 = occupancy status, A5 = PV generation, A6 = micro-wind generation, A7 = individual appliances consumption, A8 = indoor temperature, A9 = outdoor temperature, A10 = building, room and appliance characteristics.**

23	ECO [15]	2014	1 s	6	A1, A3, A4	6	8 months	Switzerland
24	GREEND [38]	2014	1 s	9	A1, A7	8	1 year	Austria, Italy
25	ADRES [2]	2015	1 s	Aggregated	A1	39	14 days	Austria
26	DRED [51]	2015	1 s	13	A1, A8, A9	1	6 months	Netherlands
22	RAE [64]	2016	1 s	24	A1	2	9 - 63 days	USA
21	UK-DALE [30]	2017	6 s & 16 kHz	4	A1, A7	5	4,3 years	UK
22	BLUED [60]	2012	12 Hz	Aggregated	A2, A7	1	1 week	USA
23	ENERTALK [58]	2019	15 - 11 Hz	1-7	A1, A7	22	30 - 122 days	Korea
24	NOVAREF [87]	2020	2 s	-	A1	12	1 year	Germany
25	IDEAL [59]	2020	1 s	19	A1, A7, A10	39 - 255	20 months	UK

TABLE 4. **Publicly available datasets of short measurements of various appliances. Each appliance was measured for short periods of time, usually an hour or less. The table includes information about the year they were published, their sampling rate, the number of submeters used, the number of houses they were measured in, the total length of time the measurement campaign lasted and the country where the measurements took place.**

#	Acronym	Year	Sampling Rate	Submeters	Features	# Houses	Period	Country
1	ACS-Fl [85]	2013	10 s	100 (10 types)	I, V, P, Q, f, U	-	1 h	Switzerland
2	ACS-F2 [87]	2013	10 s	100 (10 types)	I, V, P, Q, f, U	-	1 h	Switzerland
3	PLAID [67]	2014	30 kHz	60	I, V	11	3 month	USA
4	COOLL [86]	2016	100 kHz	46 (12 groups)	I, V	1	2 h	France
5	PSD [84]	2012	1 min	-	P	10	1 week	USA

appliances (Watts per minute/seconds/millisecond intervals). The electricity consumption of multiple appliances is measured by attaching a plug level monitor to a common plug (Watts per minute/seconds/millisecond intervals). The data is then saved locally or transmitted to a remote server and anonymised.

As mentioned above, the root causes for the low number of publicly available residential load profile datasets are the privacy concerns of the participants and, to a smaller degree, the financial constrains of such campaigns. As a rule, participants do not trust that their data will be anonymised before being analysed, leading to a sense of an invasion of or threat to their privacy. Such concerns are not entirely unfounded: if the person who analyses the non-anonymised datasets has knowledge of the number, types and load profiles of the devices in the household or long experience with analysing such datasets, they could potentially identify when each device was activated/deactivated, potentially revealing the activities of the participants in their houses. Very often, participants in measurement campaigns have requested, after participating in the study for some time, to be removed from them. Such privacy concerns are especially strong in countries with a history of state surveillance, such as Germany, and make it extremely difficult to convince people to participate in measurement campaigns in the first place, especially long-term ones lasting for several years.

As a result, all but four measurement campaigns ([21], [25], [30], [43], [65]) conducted measurements for less than four years, only two of those measured a large amount of houses ([21], [65]) and only three of those recorded measurements at high sampling rates ([25], [30], [43]). As can be clearly seen in Table 3, there are no publicly available residential load profile datasets which contain decades of measurements of hundreds of houses, with the exception of [30] which used data measured over the course of multiple measurement campaigns over more than two decades. The published product of [30], however, was the reference load profile H0 SLP rather than raw measurements, unlike the rest of the 24 datasets. Of the high resolution datasets ([2], [11], [15], [25], [30], [31], [34], [38], [40], [43], [51], [58]–[60], [63], [64], [69], [70], [88]), only one measured more than 50 houses [59] and only one dataset recorded the electricity consumption of one or more houses for more than 5 years at high sampling rates [43] (see Table 3).

The advent of non-intrusive load monitoring (NILM), otherwise known as non-intrusive appliance load monitoring (NIALM) or load demand disaggregation techniques is likely to increase privacy concerns due to its ability to disaggregate composite loads and, hence, identify the activation or deactivation of specific devices in a household whose electricity load profile has been made publicly available [61]. To combat such worries, the owners of certain publicly available datasets have made access to their data contingent on legally binding agreements which expressly forbid their usage for NIML analysis.

The extend to which models are affected from these privacy issues depends mainly on their structure and sampling rate. Bottom-up models, especially those with high sampling rates, depend strongly on the load profiles of individual appliances and their usage over time. Therefore, they are more strongly affected as it is quite challenging to, both, convince people to agree to join measurement campaigns and to prevent them from withdrawing. Furthermore, every time a new model is created, they need to expend time and money to buy and install the necessary equipment, as well as to convince individuals to join. This time and money would be better spent focusing on building their models or answering scientific/engineering questions. This would have been possible had more and better quality datasets been publicly available. Top-down models, on the other hand, especially those with high sampling rates, are affected by the relative lack of publicly available datasets with: (a) a measurement period longer than 1 year, (b) a high sampling rate and (c) a large number of measured houses (above 100). This relative lack of suitable datasets stems from the fact that it is currently very difficult to convince large numbers of people to agree to the monitoring and collection of the electricity load profiles of their houses for long periods of time.

D. SPATIAL RESOLUTION OF THE DATASETS

Another challenge the researchers face is the lack of spatial resolution information in the publicly available datasets. Due to the above mentioned privacy concerns, none of the publicly available datasets include information about the spatial distribution of the participating houses. The non-publicly available datasets could also lack any spatial information, however, since it has not been possible to access them, this is not a statement that can be made with any certainty. As a result, the effects of the different spatial distributions of households on the aggregated residential load profile are not known and have not been studied.

E. SAMPLING RATE OF THE DATASETS

The sampling rate of the existing publicly available datasets poses a different set of challenges. The majority of these datasets can be used to create models with a sampling rate of an order similar to or lower than that of the dataset used. Unfortunately, datasets with a resolution higher than 1 minute and possibly 1 second will be needed to address the challenges of demand side management and smart homes that the switch to renewable energy sources and the increased use of electronic devices, electro-mobility, social conditions and self-generation and consumption will bring. This is made clear by studying Figure 8, where it is evident that the residential load profile changes every minute/second rather than every fifteen minutes or one hour due to the usage of multiple electrical devices, from ovens to smartphones. The adoption of an ever-increasing number of electricity powered devices such as tablets, gaming-consoles and electric cars as well as the switch to electricity-powered interior heating and working (even part time) from home will only intensify these trends. A more thorough discussion on the subject can be found in [88].

F. DATA GAPS AND MEASUREMENT ERRORS

A sixth challenge is the data gaps and measurement errors contained in the recorded datasets. The data gaps are usually caused by equipment failures and/or power outages, while measurement errors can appear due to a variety of reasons, which will not be discussed here. To remove them, post-processing needs to be applied, a task that is usually very time consuming. As a result, most datasets are offered without any post-processing (e.g., [11], [72]). Datasets that have not been post-processed force the researchers to do the post-processing themselves without having any clear knowledge of the reasons for the data gaps or whether a strong deviation from the measurements was caused by a measurement error, an equipment failure or by an actual electricity consumption event. This reduces the volume of data available and complicates the process of model building.

G. LACK OF SECOND/VACATION MEASURED DATASETS

Another issue that should be addressed is the existence of second/vacation homes, whose electricity consumption patterns are distinctly different from those of primary homes. Primary residencies are characterised by high electricity consumption during the winter and low electricity consumption during the summer, as can be seen in Figure 9.

Depending on their usage, vacation residences are characterised by low or no electricity consumption in the winter and high electricity consumption in the summer with a possible increased electricity consumption also during other holiday times (when the residents vacation in the house and

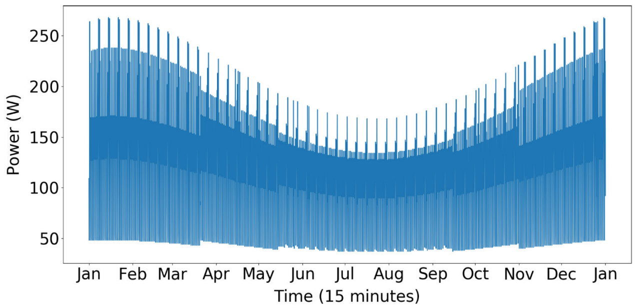

FIGURE 9. The H0 SLP yearly profile. The electricity consumption is higher in the winter and lower in the summer. The spikes depict the weekend electricity consumption while the troughs depict the electricity consumption during the week. In the H0 SLP, the weekend electricity consumption is always higher than the weekly electricity consumption. The dataset spans the time period between 01.01.2017 at 00:15 and 01.01.2018 at 00:00 [12].

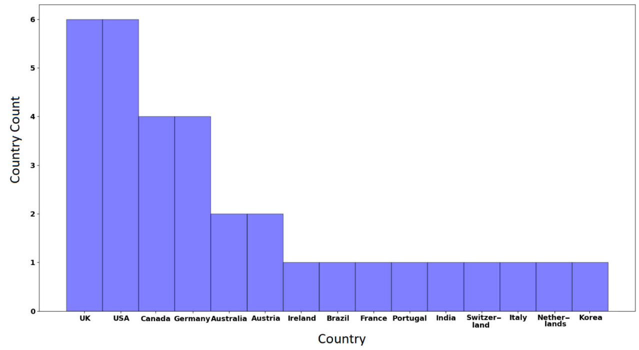

FIGURE 10. Datasets per country distribution. Distribution of the countries where the publicly available datasets were recorded. The UK and the USA have the most, closely followed by Canada and Germany. The rest have two or less datasets, with most having only one.

consume electricity). Secondary homes can either have high electricity consumption during the holidays, when the families or individuals spend their holidays there, or they can have normal electricity consumption during the week but low or no electricity consumption during the weekend if they belong to people who work in a different city than their partners and/or children and visit them every weekend.

Secondary/vacation homes might also have a different set of appliances compared to the primary homes and they might be used at different intervals than the ones used in primary homes. This would cause their electricity consumption characteristics to diverge even more. This is important as a significant number of vacation/secondary houses are located in touristic regions and/or small villages (where mini- and micro-grids are more likely to be installed). As a result, their electricity consumption patterns will not conform with those of the H0 SLP which will make maintaining the stability of these grids more challenging. They will also not conform with any of the above presented residential load profile models. These houses are rarely mentioned in the literature and are even more rarely studied (there is only one publication regarding this subject and it does not study the electricity consumption itself but rather its yearly values [4]). As expected, there are no publicly available datasets of second/vacation home electricity consumption profiles.

H. LOW NUMBER OF RECORDED DATASETS PER COUNTRY

Lastly, the electricity consumption patterns and statistical characteristics of houses located in different countries can vary strongly due to differences in GDP, different lifestyles, different device availability/characteristics, length of day and climate. This is especially true for households located in different continents and latitudes, such as the USA, Germany and India.

The countries where the publicly available datasets were measured can be seen in Table 3 and in Figure 10. As can be seen, the majority of the countries have produced no more than two publicly available datasets, except for the UK, the USA, Canada and Germany. Because even countries in the same continent (such as Germany, UK and Portugal) can have different consumption patterns if they are far enough from one another or have different enough life-styles, they cannot be used to model the same household. This results in a large reduction of the datasets available to model the electricity consumption profile of a household in a specific country.

VII. DISCUSSION

The majority of the challenges presented in Section VI can be solved by increasing the number of publicly available high sampling rate datasets. In order to achieve this, the number of high sampling rate measurement campaigns must increase and the collected datasets must be made available for further research. For this to be achieved, more funding needs to be made available for such campaigns and, more importantly, the privacy concerns of the citizens of each country must be addressed in order to increase the number of residents willing to participate in such studies and reduce the number of residents withdrawing from a study after they have participated in it for some time.

The number of measurement campaigns can increase through governments supporting and funding a higher number of such studies. The privacy concerns of the citizens can be addressed by ensuring that the data measured are anonymised before any human has access to it, through the deployment of an automated system, which will remove all identifying information and delete the original data at the end of the anonimisation process.

Unfortunately, this means that the latitude and longitude coordinates of the participating houses must be removed during the anonimisation process and no publicly available datasets can ever contain the spatial coordinates of the participating households. As a result, the only way to solve the lack of spatial information issue, would be to have the datasets clustered per city district, which might not provide enough data for researchers who want to investigate how the layout and design of low-voltage residential networks and mini-/micro-grids would affect the load profile of a residential neighbourhood.

Another possible solution is the use of a crowd-sourcing approach through the creation of a web portal where residential consumers would be able to self-upload their smart-meter-measured electricity consumption time series. In order to ensure their privacy and alleviate any concerns, the submitted datasets would need to be anonymised through an automated system like the one described above. They would then be made available to researchers. Such an approach could be supported by national governments through encouraging/financing the installation of high resolution smart meters in households. Furthermore, in order to protect their privacy, provide residents with the option to share their data and prevent privacy corporate malpractices of the type that Facebook, Google, Apple and other internet companies have committed in the past couple of years, the smart meters should give residents complete access to their raw consumption time series but only provide a 15 minute sampling rate time series to the electricity providers for billing purposes. Such an approach would promote research and, at the same time, alleviate any privacy concerns the residents might have.

A step in this direction was made by the UCL Energy Institute, which announced the creation of a ''secure, consistent and trusted channel for researchers to access high-resolution energy data'' [1]. The data will be collected from households who explicitly consented to have their data collected for research purposes and will be anonymised using ''established '5 Safes' protocols'' [1]. The database will contain the residential load profiles of potentially thousands of anonymised UK houses and will be continuously populated with new data every year. Most importantly, it will only be accessible to accredited UK or UK-affiliated researchers and, through them, accredited researchers who collaborate with them.

Another, albeit highly imperfect, solution in the absence of measured residential load datasets is the use of synthetic residential load profiles. At the moment, there are only two such publicly available datasets. The first dataset can be generated through the freely available software that Dr. Noah Daniel Pflugrad created [44]. The major drawback of this software is its sampling rate which ranges from 1 to 6 hours and is, therefore, ill-suited for high resolution residential load profile modelling. The second data set was created by Tjaden *et al.* (2015) [50]. It has a sampling rate of 1 s and is publicly available. As can be seen, there are too few publicly available synthetic datasets, which makes it a problematic solution. There are, however, many publications describing methods which can be used to generate them. Unfortunately, the source code which these publications were based on is also not publicly available. A possible solution to this problem would be making all (past and future) codes publicly available where possible. This would increase the ability of researchers to generate synthetic data sets and, by making these datasets publicly available, will increase the number of publicly available synthetic data sets.

To address the lack of data on secondary/vacation homes, the best solution is for governments and research institutes to organise and fund measurement campaigns which focus specifically on theses types of houses. The same applies for the low number of publicly available datasets for any single country.

Lastly, going forward, any residential electricity load profile dataset used to create a residential electricity load profile model should (after the proper anonymisation has been applied) be made publicly available and be licensed under a Copyleft licence [76]. This will make it possible for a) the results presented in the publication to be verified/replicated to ensure they can withstand scientific scrutiny and b) for new research on the same data to be performed.

VIII. CONCLUSION

The rise of electromobility, the surge in ownership of electricity powered devices together with the rise in the Earth's population, the advent of work-from-home and the expansion of self-generation and consumption will change the residential load profile in the coming years and decades. In order to be able to understand and forecast these changes, we must first have a solid understanding of the state-of-the-art residential electricity load profile and its modelling. This understanding is unfortunately sorely missing, as this review has shown. An extensive literature research, which assessed the current state of residential load profile modelling, managed to identify only thirty two residential electricity load profile models.

At the beginning of the review, a universal definition of the residential load profile model is constructed and the criteria that it must fulfil are presented. Because no single search engine contained all the publications, both Google scholar and the Web of Knowledge are used. After filtering for unrelated disciplines, conformation to the above mentioned definition and duplicates, the number of relevant studies is reduced to thirty two, a very small number when compared with, e.g., energy consumption models (that do not differentiate between electricity and fossil-fuel energy consumption) which, according to Swan *et al.* [49], numbered 252 in 2009.

Up to this point, residential electricity models were only divided into two broad categories: bottom-up and top-down models. When the main features of all thirty two models are considered, it becomes clear that a much more nuanced categorisation is necessary. In this review, a new categorisation system is proposed based on the identification of the main features of the thirty two studies. The models can be divided into four main categories based on the a) methods used in the model, b) the sampling rate of the model, c) the intended application of the model and d) the statistical techniques used in the model. Each category can then be subdivided into three to four subcategories, depending on the forms that the model features can take.

Future residential load profile models can be used to research and facilitate the operation of energy neutral Smart Houses or help reduce their electricity consumption and/or energy bills through demand side management and load shifting. They can also research and help maintain the stability of mini- and micro-grids through load shifting or demand forecasting of the small groups of houses, neighbourhoods or small villages belonging to these grids. They can also be used as part of a larger mini- or micro-grid model or a city-wide grid model to maintain the grid's stability and help identify the best technologies that can be used to that end by providing accurate residential electricity load profiles. Lastly, they can be used to study how the addition of new devices, vehicles, work-from-home, building technologies and standards will affect the residential electricity load profile and create short and long term forecasts.

Researchers who attempt to build residential load profile models face multiple challenges, the most important of which are: a) the unsuitability of the BDEW SLP, b) the non-public nature of the model source code, c) the spatial resolution of the recorded datasets, d) the sampling rate of the recorded datasets, e) the presence of data gaps and measurement errors in the datasets, f) the lack of second/vacation recorded datasets, g) the low number of recorded datasets per country and h) the most important of all and the root of most of the previously mentioned challenges, the privacy concerns of the individuals who are approached to participate or are already participating in measurements campaigns.

The majority of the previous challenges could be easily rectified if the participants and/or the individuals asked by researchers to join such campaigns were not concerned that the collected data could be used to identify when individual devices were turned On/Off in the household. These concerns could be easily rectified by automating the anonymisation process, thereby ensuring that no human would come in contact with the recorded datasets before all spatial and identifying information are removed. Erasing the raw data at the end of the anonimisation process would further allay any concerns that the participants or potential participants might have and potentially increase the number of participating houses in the process.

It is, therefore, imperative that governments and research institutes create mechanisms that ensure the anonimisation of the data recorded during measurement campaigns and provide the funding necessary to do so. Another possibility would be to encourage the public to install smart meters with high sampling rates in their houses, while ensuring the privacy of the participants by giving them access to their data, restricting the access of the electricity providers to the raw data and allowing the participants to share only as much data as they are comfortable with. They could further encourage a crowd-funding approach where individuals would be able to upload their own electricity consumption datasets on a web portal, where after all identifying information has been stripped from the datasets, they could be made available to researchers. A step in this direction has already been made by the UCL Energy Institute in the UK through the Smart Energy Research Lab project.

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