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A Survey-Assisted Time-Domain Characterization of the Power Patterns of Main Household Appliances

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Abstract

The characterisation of power curves for individual household appliances needs to consider technical and user behaviour-based aspects. To assess the impact of an aggregation of appliances, the combination of non-synchronised power curves of multiple appliances with different types of usage in different households has to be represented. This article sets up a framework of analysis that incorporates survey-based indications on the user's behaviour, taken from a dedicated questionnaire, and the measured characteristics of main appliances with user-based activation. A Monte Carlo approach is formulated to determine the specific contribution of a given number of similar appliances to the aggregate power curve. Examples are shown, considering examples taken from the aggregate usage of washing machines and dishwashers as two exemplificative types of main household appliances with user-based activation. The analysis is then extended to power curves defined with different time steps to determine indications such as the peak power and the 99% and 95% non-exceeding probability of the aggregate demand for the same type of appliances. The availability of information on the aggregation of the main appliances is useful to refine demand response programmes and assess the interaction between appliances, local generation and local storage in the household.

Keywords: aggregation; consumer preferences; dishwasher; household appliance; Monte Carlo analysis; questionnaire; washing machine

1. Introduction

Load pattern analysis for electricity users considers the time series of the average power represented for successive time steps typically of regular duration, also denoted as the power curve. The characterisation of the electrical loads with power curve models is crucial to analyse how and when electricity is used, reproducing the shape of the consumption of all devices powered by electricity. The assessment of the users' demand is essential for managing grid efficiency; preventing overloads; optimising the operation by also considering electricity price variability; and integrating renewable energy sources, heat pumps and home chargers for electric or hybrid vehicles [1]. Among the different types of demand, the residential load (essentially, the electricity demand of households) represents about 30% of final electricity consumption within the European Union [2]. Until a few years ago, the residential load was considered mostly independent of the socio-economic context of the members of the household, also being highly unpredictable and therefore difficult to model [3]. More recently, the participation of the users in shaping the overall

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demand of electricity has received specific interest, also due to advances in smart metering, which has highlighted how residential load demand changes during time by identifying the contributions of the individual users to the residential load pattern in a more specific way, paving the way to large-scale statistical analyses supported by real-time data.

Nowadays, the residential electricity sector has evolved to a complex structure, integrating the following features:

- *Home automation*: This includes devices integrated into home management systems connected to each other and to a network that enable the automation and control of the system, improving the comfort, energy efficiency, and security of the home [4].
- *Self-generation systems*: Local systems to produce electricity for residential consumption are increasingly present. They allow higher independence from the traditional electricity grid, reducing costs and environmental impact. The optimal use of self-generated energy can be achieved using advanced control systems and technologies [5].
- *Multi-energy interactions*: The main appliance that can enable effective decarbonisation in households is the heat pump, which requires overcoming barriers (mainly financial) for facilitating its diffusion [6].
- *Home storage systems*: Storage batteries allow residential customers to store self-generated energy and use it in an efficient way, also considering possible benefits to increasing reliability and resilience of the electricity supply to the household [7].
- *Home wallbox*: Electric vehicle charging stations are a key element for home charging, impacting the load profile [8].

In this context, the residential demand can be partitioned into different types of loads depending on their control mode. On the one side, there are *temperature-based* loads (e.g., refrigerators and electrical heating and cooling devices) that operate under thermostatic control and depend on the user's settings and on the ambient conditions. On the other side, there are *controllable* loads with user-defined activation, which can be partitioned into [9]:

- *Deferrable* loads, in turn classified into *non-flexible* loads (e.g., washing machine or dishwasher) with a predefined pattern that depends on the scheduled settings and cannot be altered during the operation time, and *flexible* load, such as plug-in electric vehicles with smart home charging, for which the schedule can be modified over time.
- *Curtailable* loads, in turn classified into *partially curtailable* loads (such as lighting, for which the power demand can be changed by arranging the load into groups that can be activated totally or in part), or *fully curtailable*, which can be switched on or off depending on the consumer priorities and comfort constraints (e.g., water heaters).

With reference to the power curve, by definition, deferrable loads are controlled by shifting their operation on the *time* axis only, whilst curtailable loads are controlled by changing their amplitude on the *power* axis only. However, the classification into deferrable or curtailable loads is not rigid. Some loads can be both deferrable and curtailable (e.g., plug-in hybrid electric vehicles subject to smart charging may have a flexible operation in which the charging can be modified both in time and amplitude during a period, subject to the constraint that at the end of the period, the state of charge must be restored above a user-defined minimum, with an impact on the appliance modelling [10]).

Besides the technical aspects of the electricity demand characterisation, for residential users there is a strong need to consider the user's behaviour, taking into account how the user's behaviour, lifestyle and preferences impact the shape of the power curve for individual appliances and aggregate demand. The most efficient way to obtain this kind of information is to contact the users, asking them to give their responses to specific questions prepared to assess dedicated aspects of electricity consumption. The integration of technical information on the characteristics and usage patterns of residential appliances with the opinions of the users makes it possible to carry out more informed studies on the overall impact to the residential demand in the energy system.

1.1. Literature Review

The availability of the power curves of residential users is important for the implementation of residential electricity policies like demand response programs, tariff design, and incentives for increasing the energy efficiency [11].

In this respect, the literature has considered different kinds of analysis, aimed at investigating the overall residential demand, or dedicated to the study of individual household appliances.

1.1.1. Overall Residential Demand

Considering the overall residential demand, a residential load profile model has been 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" [3]. Residential load profiles present a high degree of variability not only because of their strict dependence on the inhabitants' lifestyles and habits but also on climate, physical characteristics, owned and used appliances, and in general on occupant behaviour. As a consequence, it is difficult to accurately predict load profiles and also to set up accurate models. For this purpose, the identification of the residential load profiles has been carried out through appropriate segmentation of the main energy uses in the residential sector, which can be categorized into [12]:

- Space heating and space cooling: provide energy for maintaining the living space at a comfortable temperature and air quality.
- Domestic hot water: provide energy for heating water to an appropriate temperature.
- Appliances and lighting: provide energy required to operate common household appliances and for adequate lighting of spaces.
- Mobility-based models: provide energy for home charging of electric vehicles.

On these bases, residential load profile models can be categorized into [13]:

(i) *Bottom–up* models: These are based on the detailed load profiles of individual end-users that are aggregated to obtain the profile for groups of end-users.
(ii) *Top–down* models: Top–down residential load profile models are based on aggregate data, and, by means of statistical approaches, information at low levels can be obtained.
(iii) *Hybrid* models: These combine bottom–up and top–down models.

Bottom–up residential load profile models are based on the detailed power curves of individual end-users that are aggregated to obtain the profile for groups of end-users (also at regional and national levels) [3,12]. When applying such an approach, the basic element is the individual load. By aggregating the data acquired for each electrical load, it is possible to identify the consumption for each user, group of users, and so on. When, in addition to the electrical data, further indications are available on demographic information (user located in an urban, extra-urban, or rural area), geographic–territorial information, the type of user (number of occupants and type of electricity supply contract), the habits of the user's household, the characteristics of the home (size, construction materials), weather conditions, and so on, a very detailed electrical load profile for each home can be identified [14]. The advantage of the bottom–up approach is, therefore, the ability to profile the model in detail, given the large amount of information processed. However, this is also one of the disadvantages of the approach, because of the computational burden of the models. An issue related to the privacy of the end-user arises, because data must be stored and managed appropriately. The bottom–up model is suitable to set up a Monte Carlo simulation for building an aggregate load profile for a residential area [15]; the Monte Carlo approach allows one to account for the variation in some inputs, such as house occupancy and appliance usage. More recent contributions make use of load profile models to evaluate the flexibility in the residential sector, for instance, proposing a bottom–up load model that includes weather and user behaviour to obtain yearly time series [16].

Top–down residential load profile models are based on aggregate data, and, by means of statistical approaches, information at the appliance level can be obtained. Examples of inputs are total electricity consumption, the structural characteristics of the houses, characteristics of occupants, and climate and macro-economic indicators [3,12]. Top–down models do not need to collect information about individual electric appliances (as bottom–up requires) and do not require heavy computational efforts; on the other hand, their application relies on the availability of historical data of household electricity consumption [3]. Top–down models can help system operators evaluate demand response actions. A method to obtain load profiles based on smart metering data is presented in [11], aimed at building aggregate residential load curves for different day types, seasons, and climate zones using a real-world hourly smart meter dataset.

1.1.2. Individual Household Appliances

The analysis of household appliances can be carried out in different ways [17]:

(a) At the *appliance level* to get the technical characteristics of the household appliances that are combined with occupancy and lifestyle data to form the basis for the application of a bottom–up model [10]. The results are used for assessing the impact of the household appliances for integration of the residential demand in the grid or for the development of residential demand simulators [18].

(b) At the *point-of-connection level*, starting from measurements gathered for the overall household and applying procedures for electric demand disaggregation, typically through Non-Intrusive Load Monitoring (NILM) [19].

In NILM applications, measurements of voltage and current are taken at the point of connection to determine the total power of the aggregation of appliances. The contribution of the appliances is then reconstructed through the application of suitable algorithms without the need for measuring the individual appliances. With NILM it is also possible to obtain indirect information on appliances not easily accessible with direct measurements.

NILM techniques are based on identifying the "signatures" of the different types of appliances [20]. An essential point can be to extract information from the occurrence of events, which mark the connection or disconnection of a new appliance, considering the corresponding change in amplitude. For this purpose, the literature proposes several techniques, whose review is outside the scope of this article. At a general level, unsupervised NILM approaches require the preliminary knowledge of appliance models to be compared with the measurements, while supervised NILM approaches require a first training phase in which the time series are compared with known outcomes, followed by the evaluation phase in which the actual data are used. Semi-supervised approaches have also been formulated. Concerning the features to be used, many approaches are based on data gathered at high sampling rates (e.g., at sampling frequencies of the order of kHz) to capture better information, also including features taken from harmonics [21]. Recent developments include neural network-aided NILM for appliance disaggregation using a sequential subtraction method [22], the transformation of low-resolution time series into images processed with a multimodal data fusion-based vision transformer [23], and the multi-appliance approach for simultaneous disaggregation of multiple appliances by identifying common features and individual features [24].

Progress in the studies on individual household appliances is also facilitated by the increasing availability of specific datasets, taken from systematic surveys [25] or from dedicated repositories (e.g., Pecan Street [26], IEEE Dataport [27], REFIT [28], and others; see for example [21,29] for an extended list). Recent surveys that take into account the characteristics of the appliances used in specific regional contexts have been reported for example for China [30], Japan [31], and Burkina Faso [32].

Considering the potential for demand reduction, in a study carried out in the Midwest region of the U.S. based on a survey with 376 valid responses [17], for most times of the day, clothes dryers have shown to be the most promising, followed by dishwashers and washing machines. Dishwashers, dryers and washing machines also emerged as appliances with higher variability during the day in a study carried out on new single-family homes in Texas [33]. Dishwashers, washing machines and dryers are also addressed in a survey that focuses on the habits of the occupants in German houses [34].

1.2. Research Gaps

As a general consideration, while top–down approaches may fail in capturing the behaviour and preferences of end-users, bottom–up approaches may fail in case of limited sample sizes of available data of end-users [11].

There is a lack of methodologies formulated for addressing the impact of individual types of appliances on the aggregation of the same type of appliances. The challenging aspect is that the effective application of such a methodology requires the collection of information from the users, together with a characterisation of the household appliances that includes knowledge on different modes of operation (e.g., programmes of usage), because identifying an appliance with a single power curve is too limited to take into account realistic situations.

Another specific point that has been rarely considered is the definition of a suitable time step to represent the power curves of the individual appliances. On the one hand, the signals can be gathered inside the measuring systems with high frequency, but for the purpose of the analysis of the electrical demand, such a high resolution is not needed, as there will be too much data to communicate, and knowledge of very fast variations in the time series does not add significant elements to identify the usage patterns. Establishing suitable time steps depends on the nature of the demand in the specific context (the household appliances in this case).

1.3. Contributions of the Article

Considering the research gaps previously indicated, this article refers to shiftable household appliances and presents an integrated procedure for analysing the power curves of the main appliances by combining technical information with user behaviour information gathered from a specific survey carried out through a questionnaire sent to a sample of users.

The specific contributions are as follows:

- This study focuses on individual types of shiftable appliances with user-based activation to provide an informed view of the contribution of each type of appliance to the power curve of an aggregate group of users. This focus is different from classical ways of addressing the whole residential load profile or the individual household appliances in bottom–up or top–down approaches.
- This study provides a representation of the power curves of individual types of household appliances based on the measurements carried out on the appliances and on the information on the time for starting the appliances, elaborated from the outcomes of the questionnaire sent to the users.

- This study provides the formulation of a statistical approach based on the Monte Carlo method for the construction of the user behaviour-based aggregation of the same type of appliances for different time steps. The results are the statistics of the peak power and different percentages non-exceeding probability of the aggregate power of the selected type of household appliance.
- This study provides a comparison of the results obtained on the statistical characterisation of the power curve by considering measured data representations at different time steps.

1.4. Article Organisation

The next sections of this article are organised as follows. Section 2 starts with presenting the structure and results of the questionnaire sent to the users to obtain information on the starting time of the main controllable appliances with user-based activation installed in the households. Section 3 discusses the measurement carried out on the individual appliances and the characterisation of the power curves at different time steps. Section 4 describes the proposed procedure for aggregating the power curves of the same type of household appliances based on the outcomes of the questionnaires filled by the users. Section 5 reports the application of the proposed procedure to some exemplificative case studies. Section 6 includes a discussion on the specific findings of the proposed approach. The Section 7 contains the conclusions.

2. End-User Questionnaire

An end-user survey has been conducted in the framework of the Research Project EU-DREAM [35] to collect information directly from end-users about their habits in using typical household appliances with user-based activation. The survey has been carried out with the formulation of a questionnaire to gather detailed information on the operation of various household appliances that are managed directly by the users. The aim has been to understand the nature of the patterns of electricity consumption at the household level and support the development of accurate electrical power curves that represent the aggregation of specific types of appliances. With this information, a database has been created where user-based information on the usage of the main appliances has been collected to be used for making further statistical analyses.

The questionnaire was structured into two main sections. The first section was aimed at collecting basic information about the respondent (i.e., country of residence, type of area, number of housemates, and contract power). The second section was structured to collect information about the starting time of use (i.e., hours from 1 to 24) for each appliance by the respondents for each day of typical weeks in the winter, autumn/spring, and summer periods. The appliances included in the questionnaire were air conditioner, dishwasher, dryer, electric water heater, iron, oven, vacuum cleaner, wallbox, and washing machine. At the end, an open text box allowed the respondents to share comments and/or suggestions.

The responses collected in the end-user survey came from 523 (unpaid) Italian respondents and were then processed. In particular, a filtering process has been implemented to select only reliable responses. Different filtering criteria have been tested. At the end, the following conditions have been considered in the analysis of the results:

- Responses with a response time of less than 1 min have been discarded.
- Responses with a response time between 1 and 5 min have been evaluated to assess their consistency.
- Responses with presumably inconsistent data (e.g., use of oven, iron, etc., during the night, and use of some appliances at all the hours in a day, etc.) have been discarded.

The responses that met the filtering criteria (341 out of 523) were then analysed to obtain, for each day, hour by hour, the probability density function (PDF), such that the probability over an entire day is equal to unity.

The statistical significance of the questionnaire has been assessed by considering the assessment carried out without knowing the actual size of the population of users. In this case, the formulation used to determine the representative sample size, S (number of respondents), is taken from the basic theory of statistics [36]:

$$S = \frac{\frac{p\ (1-p)}{e^2}\ z^2}{1 + \frac{p\ (1-p)}{e^{2N}}\ z^2} \tag{1}$$

which includes the following entries:

- The total number, N, of individuals in the relevant population.
- The z-score, z, defined for a given confidence interval with the classical hypothesis of normal distribution of the data. For example, the 95% confidence interval corresponds to a z-score of $z = 1.96$.
- The proportion, p, of interest of the population for the purpose of the analysis.
- The error margin, e, that is assumed to be acceptable for the confidence interval considered.

In the application presented in this article, the population of interest can be considered as the number of families in Italy, which is over 26,000,000 according to the data provided by the Italian Institute of Statistics (Istat) for the year 2024. For such a large number, the lower side of Equation (1) becomes very close to unity, so that only the upper part of the equation is used. In addition, the term p is assumed to be equal to 0.5, for which the product, $p(1-p)$, is maximum (equal to 0.25). On these bases, taking $z = 1.96$, the relation between the sample size, S, and the error margin, e, becomes the following:

$$S = \frac{p\ (1-p)}{e^2}\ z^2 = \frac{0.96}{e^2} \tag{2}$$

The questionnaire was sent to the users with the aim of obtaining an error margin indicatively lower than 5%. In fact, with $S = 523$ respondents, the error margin computed from Equation (2) is $e = 4.3\%$. After filtering, with 341 respondents, the error margin increases to 5.3%, which is still considered acceptable due to the accurate filtering conditions applied to the responses. Figure 1 shows the relation between the error margin and the number of respondents.

Separate PDFs have been determined by grouping weekdays (Monday to Friday) and weekends (Saturday and Sunday) and for different seasons. For example, Figure 2 shows the PDFs of the starting hours of the washing machine for the weekdays in the winter season. The graph shows that the hours with the higher probability are 10 (in the morning), 19 and 20 (in the evening).

Likewise, Figure 3 shows the PDFs of the starting hours of the dishwasher for the weekdays in the winter season.

It is worth noting that aggregate results represent the users' habits in operating household appliances. Using the results of specific (and anonymous) surveys does not need neither the expensive installation of smart meters in end-user houses [11] nor the use of sensitive data.

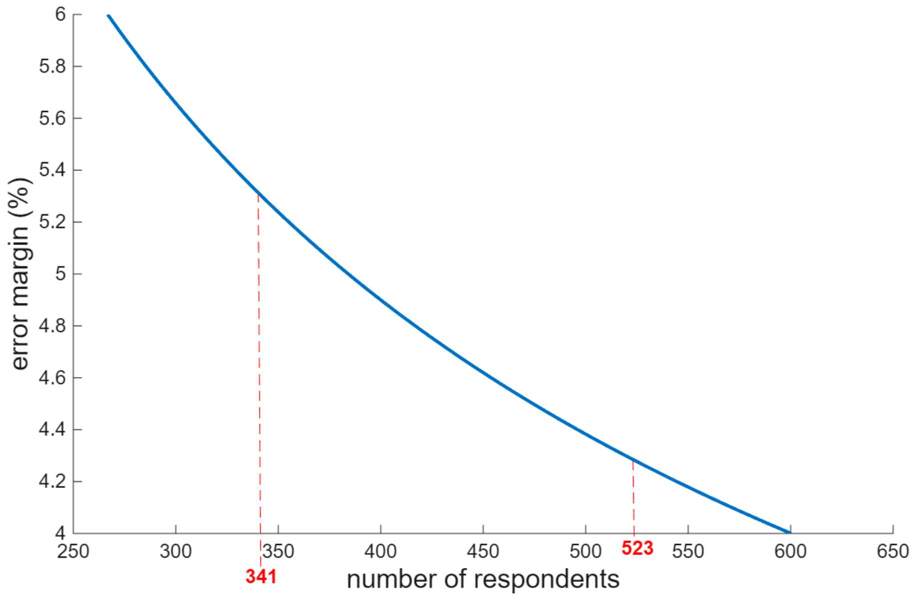


Figure 1. Relation between the error margin and the number of respondents for 95% confidence interval.

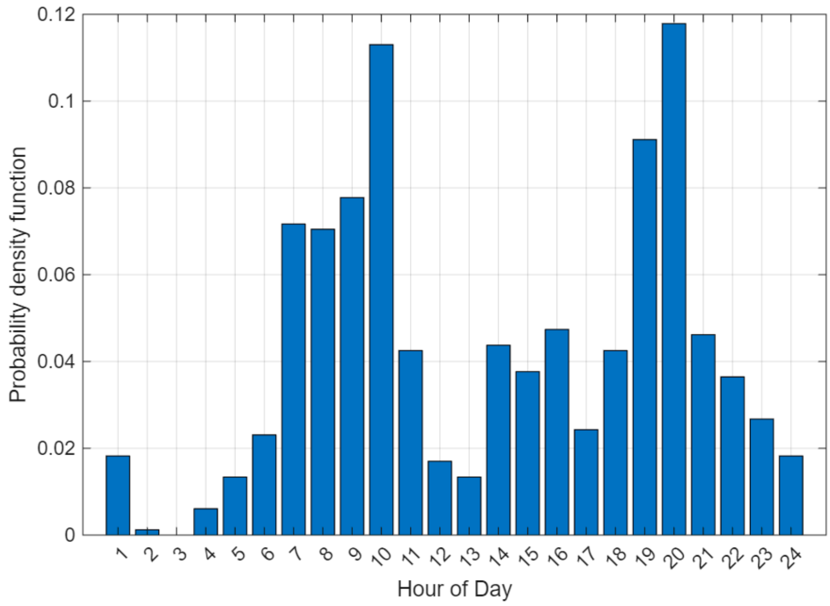


Figure 2. Probability density function for the starting hours of washing machines in the weekdays of the winter season (Italian respondents).

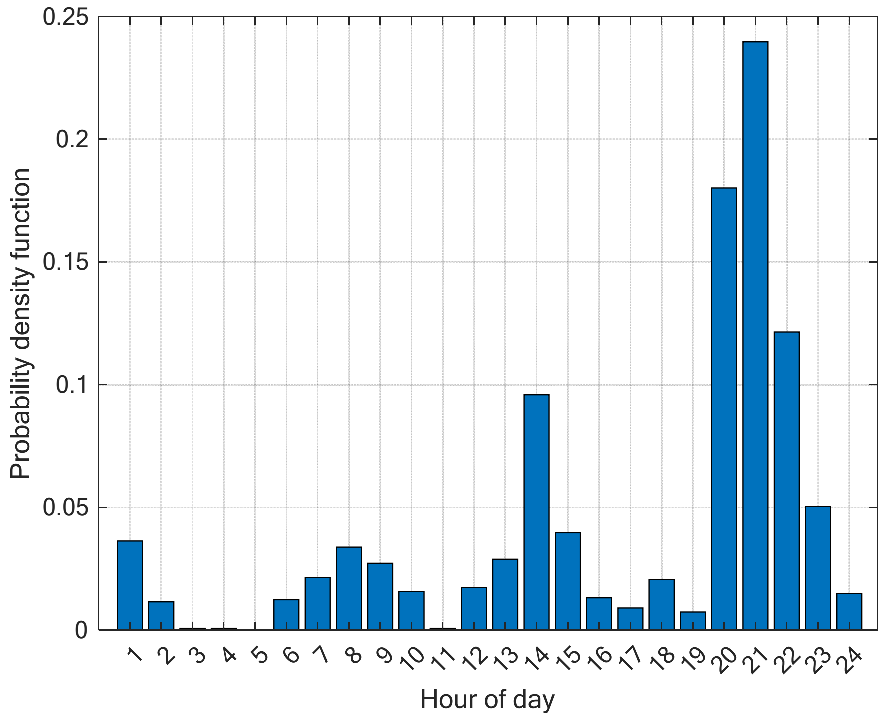


Figure 3. Probability density function for the starting hours of dishwashers in the weekdays of the winter season (Italian respondents).

3. Creation of Power Curves at Different Time Steps

The power curves of the individual household appliances with user-based activation have been taken from active power measurements. In this article, the focus is set on the methodology adopted to create the power curves for an aggregation of the same type of household appliances. Each type of household appliance is considered independently of the other ones.

Without loss of generality, a detailed analysis is presented for two types of household appliances:

(1) The first is washing machines, with measurements gathered from direct measurements on the user's appliances, by using a data logger with resolution in time of 1 s and resolution in power of 0.1 W, for a time interval corresponding to the operation of the household appliance. Figure 4 shows some examples of the power curves measured for washing machines. It may be noticed that the curves differ both in amplitude and in the duration of the washing cycle.

(2) The second is dishwashers, with data taken from a publicly available database [27], with resolution in time of 1 s. Figure 5 shows some examples of the power curves used for dishwashers.

As indicated at the end of Section 1.1.2, washing machines and dishwashers are typical household appliances with high variability, together with the dryer (which has not been considered because of its relatively low diffusion in the surveyed sample).

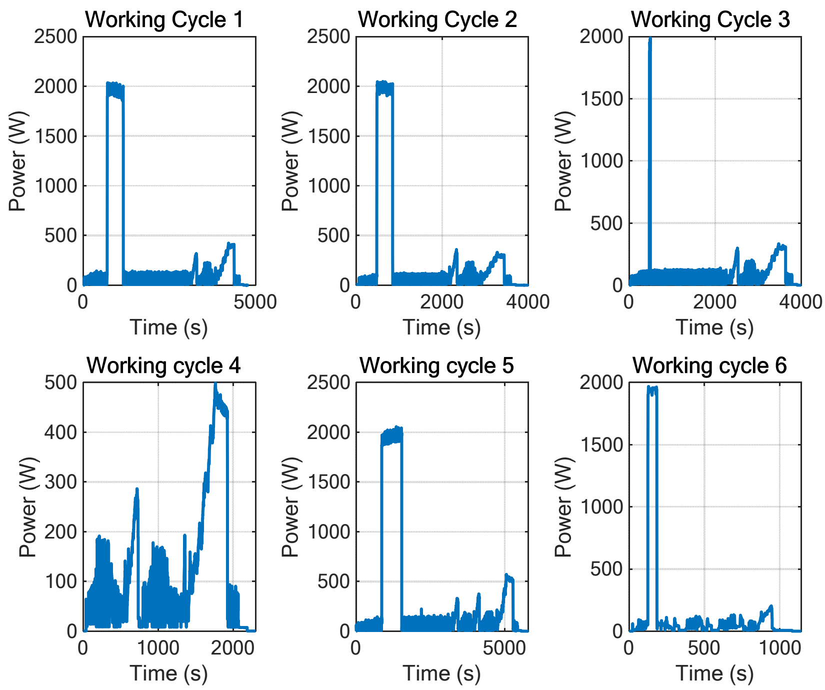


Figure 4. Examples of measured power curves of washing machines.

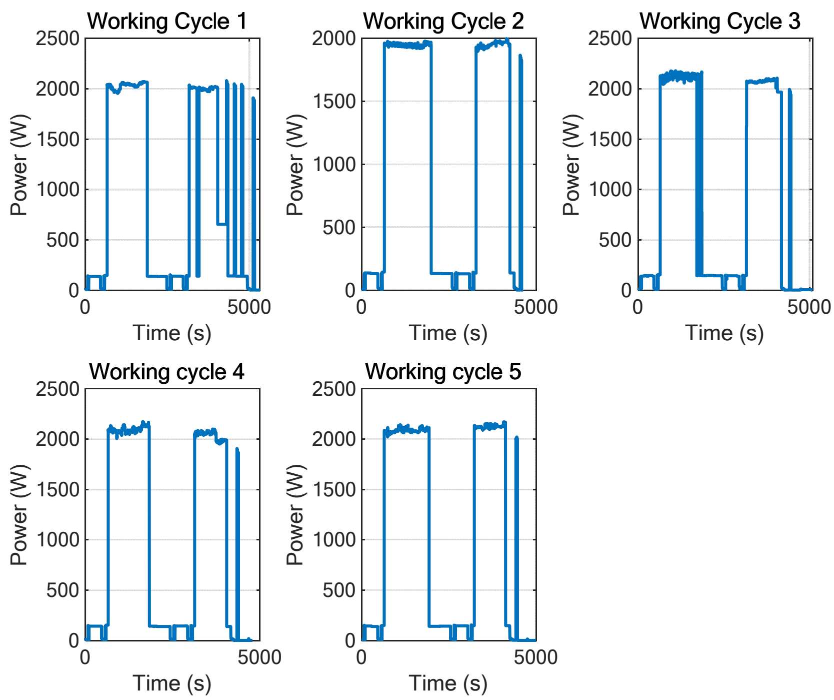


Figure 5. Examples of power curves of dishwashers.

By considering the elementary time step, τ = 1 s, for the available pattern, other active power patterns have been formed with time step multiples of the elementary time interval. In general, the average power at each time step is determined by averaging the corresponding number of successive elementary time steps [37]. By considering $m = 1, \ldots,$ and M successive blocks with $n\tau$ points in each block, the average power, $P_{n\tau}^{(m)}$, in each block is calculated with the following:

$$P_{n\tau}^{(m)} = \frac{\sum_{q=(m-1)n\tau+1}^{mn\tau} \left| P_{\tau}^{(q)} \right|}{n\tau} \quad (3)$$

In this article, the following time steps are considered:

The *initial pattern*, $\mathbf{x}_\tau = \{P_\tau^{(k)},\ k = 1, \ldots,\ N_\tau\}$, represents the pattern containing the average power data gathered in a regular way at time steps equal to the elementary time interval, τ, where N_τ is the number of elementary time intervals that contain the data points.

The *reconstructed pattern*, $\mathbf{x}_{n\tau} = \{P_{n\tau}^{(k)},\ k = 1, \ldots,\ N_\tau\}$, is considered, where n is the multiple of the elementary time interval considered for averaging the active power of n consecutive elementary time intervals. The key point is that the reconstructed pattern is formed by averaging, yet for the sake of comparison among the patterns, all the active power values are stored in the vector, $\mathbf{x}_{n\tau}$, that contains the same number of points of the initial pattern (i.e., by repeating for n times each active power value averaged at $n\tau$, so that

$$P_{n\tau}^{(k)} = P_{n\tau}^{(m)} \text{for } k \in [(m-1)n\tau + 1, mn\tau] \tag{4}$$

Figure 6 shows an example of reconstructed patterns for one of the power curves of a washing machine for n = 60 (1 min) and n = 900 (15 min). In this case, the results show that the reconstructed pattern at 1 min is able to maintain most of the characteristics of the initial load pattern, while the reconstructed pattern at 15 min cannot follow the evolution of the power curve in a satisfactory way, resulting in particular in a remarkable underestimation of the peak power during the appliance operation.

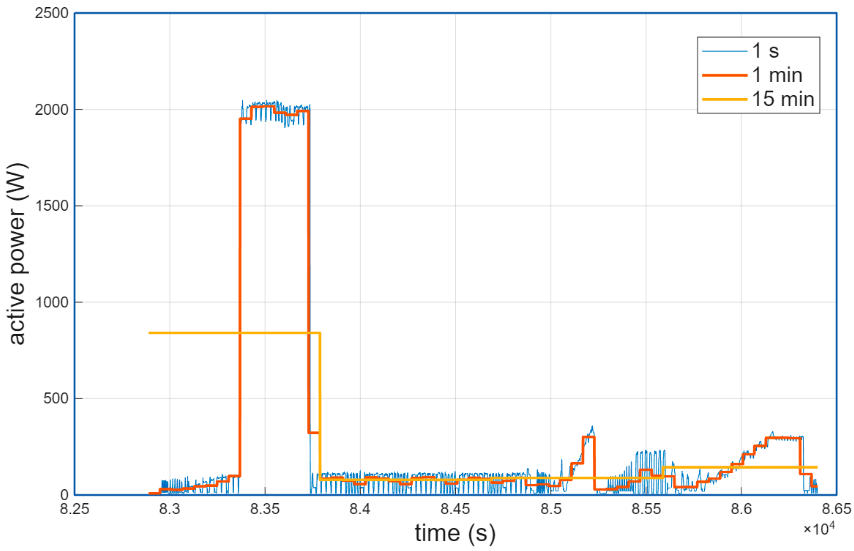


Figure 6. Patterns for the measurement of a washing machine at 1 s (initial) and reconstructed patterns at 1 min and 15 min.

Figure 7 shows an example of reconstructed patterns for one of the power curves of a dishwasher for n = 60 (1 min) and n = 900 (15 min). Also in this case, the reconstructed pattern at 1 min looks reasonable, while the reconstructed pattern at 15 min is poorly effective. In terms of peak power, the duration of the operation at almost constant values of high power is comparable with a time step of 15 min, so that the peak power found is not so different in the reconstructed patterns at 1 min and 15 min.

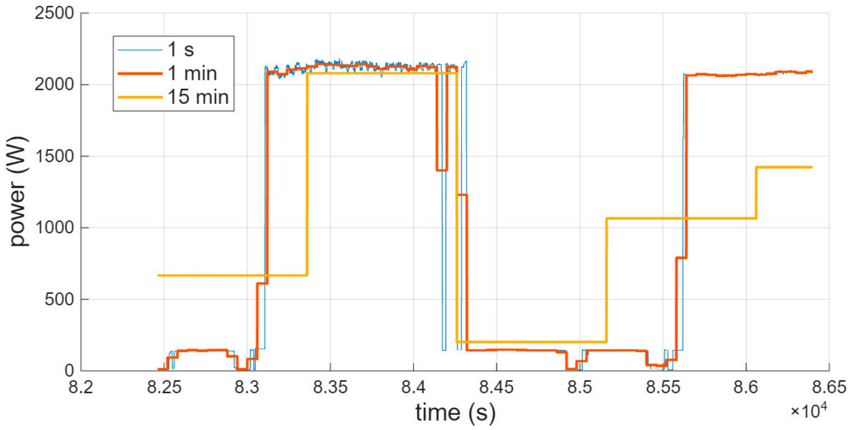


Figure 7. Patterns for the measurement of a dishwasher at 1 s (initial) and reconstructed patterns at 1 min and 15 min.

4. Probabilistic Assessment of the Aggregate Power Curve of Household Appliances of the Same Type

The load curve model is based on the results of the survey (Section 2) and on the measurements of load curve profiles for household appliances of the same type. On these bases, the proposed procedure for probabilistic assessment is applied to a set of household appliances.

4.1. Aggregate Power Curve with Initial Patterns

At first, the procedure is explained with respect to a set of, C_e, appliances of the same type, e, and a single appliance is referred to as c_e (with $c_e = 1, \ldots, C_e$). For an appliance of type e, N_e load curves are available to present a variety of working/duty cycles of the appliance; for instance, considering a washing machine, the power absorbed during N_e different washing programs has been registered, and, therefore, N_e load curves are available.

The objective of the procedure is to collocate the load curves of the appliances on the time axis of the day sampled per second into a matrix, $\mathbf{P}_e$, whose size is ($N_t \times C_e$), being N_t, the number of seconds in the period of analysis (e.g., 86,400 s for one day). Notice that N_t is a given value for the overall analysis and is different from the N_τ introduced in Equation (3), which refers to the operating period of an individual appliance that belongs to a set of appliances of the same type.

In the evaluation of each column, there are some inputs to be assigned:

(i) The starting time of the appliance considered.
(ii) The type of the load curve selected for the considered appliance.

Regarding the first point, the starting hours have to comply with the probability distribution obtained, for appliances of the same type, from the responses to the end-user questionnaire. Since the data resulting from the questionnaire are hourly based, after a random selection of the hour to consider, a further step is required to randomly generate the second (in the selected hour) in which the appliance is switched on, taken randomly from a uniform probability distribution within the hour.

Regarding the second point, the power curves of different working cycles for common household appliances are available (measured or taken from the database on a second-by-second basis in the initial power curve). A random choice among the available power curves of the same type of appliance is made.

The matrix, $\mathbf{P}_e$, is initially empty and is filled in by adding the contributions of the $c_e = 1, \ldots, C_e$ power curves, one at a time in the corresponding column. Figure 8 shows an intermediate step of the process, in which the location in time of the power curve (initial pattern) of the appliance, $c_e = 3$, is introduced, starting from the selected second (the power curve introduced is marked in red; it is assumed that the power curves of the appliances in columns 1 and 2, marked in blue, have already been introduced).

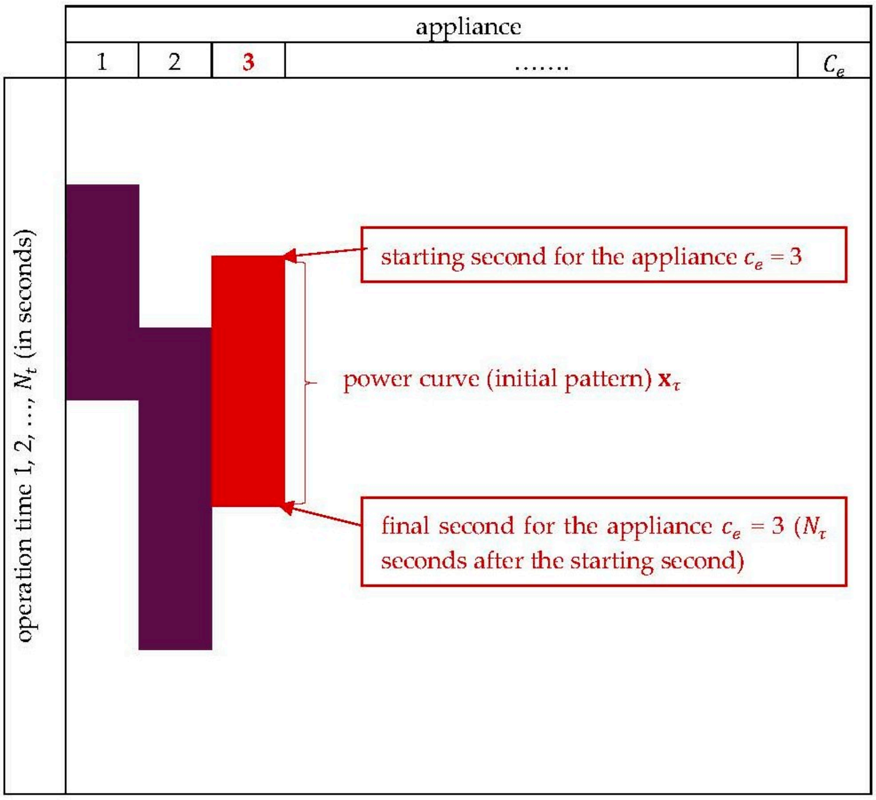


Figure 8. An intermediate step in the formation of the matrix, $\mathbf{P}_e$, for a set of household appliances of the same type—example for the appliance $c_e = 3$ (in red colour).

Once the matrix, $\mathbf{P}_e$, has been filled in completely, the following quantities can be evaluated:

(a) The *total power*, $\mathbf{p}_{\mathrm{tot},e} = \left\{P_e^{(\nu)},\ \nu = 1, \ldots, N_t\right\}$, absorbed by the C_e appliances over the day (vector with N_t values).

(b) The *maximum* (*peak*) *power*, $P_{\max,e} = \max\limits_{\nu=1,\ldots,N_t}\left\{P_e^{(\nu)}\right\}$, required by the C_e appliances during the day and the time instant, ν_e^*, corresponding to the peak power.

(c) The percentiles, $P_{x\%,e}$, of the non-exceeding power of the C_e appliances during the day, where $x\%$ is the non-exceeding probability (e.g., $x = 95$ for the 95% non-exceeding probability).

To obtain the statistics of the indicators introduced above, a Monte Carlo procedure is established. It consists of executing the procedure explained above for M repetitions. The analysis carried out in this article does not simply sets out M to a relatively large number (e.g., $M = 1000$) but provides a statistically justified termination criterion for the Monte Carlo assessment that leads to the number M of repetitions, as illustrated in Appendix A.

For each Monte Carlo repetition, $m = 1, \ldots, M$, labelling the total power as $\mathbf{p}_{\mathrm{tot},e}^{(m)}$, the corresponding outcomes are saved as $P_{\max,e}^{(m)}$ and $P_{x\%,e}^{(m)}$ for the $x\%$ non-exceeding probability of the aggregate power.

At the end of the Monte Carlo repetitions, the statistical elaboration of the outcomes leads to the determination of the related cumulative distribution functions (CDFs).

https://doi.org/10.3390/en19041014

The flow chart in Figure 9 summarizes the main steps of the procedure. The procedure can be easily extended to be applied to a set of different appliances to consider a more complex system.

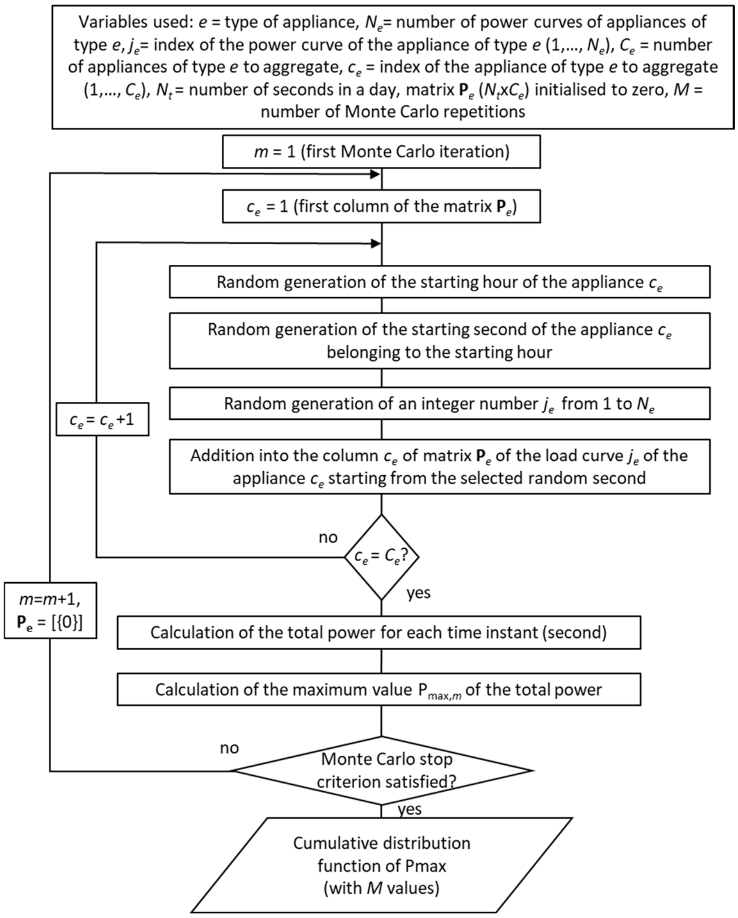


Figure 9. Flow chart representing the Monte Carlo simulation for the aggregation of a group of household appliances of the same type.

4.2. Aggregate Power Curve with Reconstructed Patterns

The procedure shown in Section 4.1 is applied in the same way also in the case of the reconstructed patterns. Since the reconstructed patterns are represented on a second-by-second basis, it is sufficient to replace $\mathbf{x}_\tau$ with $\mathbf{x}_{n\tau}$ in the formation of the matrix, $\mathbf{P}_e$.

5. Results

The procedure explained in Section 4 has been applied to some exemplificative case studies. As indicated before, two types of household appliances have been taken, namely, washing machines (Case study 1) and dishwashers (Case study 2). Moreover, weekdays in the winter period are considered.

The power curves of typical cycles have been measured in Italian houses for washing machines and have been taken from [27] for dishwashers. In both cases, the time step in the initial power curve is 1 s.

The code of the procedure has been written in Matlab 2025b. For statistical calculations, to ensure repeatability of the results, the seed for random number extraction has been assigned with the instruction rng(0).

5.1. *Case Study 1—Washing Machines*

5.1.1. Initial Load Patterns for Washing Machines

This case study presents the results of the aggregate power curve of C_e = 200 washing machines with a 1 s time step. The CDF of the starting hours of washing machines is shown in Figure 10 based on the questionnaire responses from Italian respondents and for weekdays in the winter season. The power curves that describe the operation cycles of the available set of washing machines (some examples have been shown in Figure 4) have been considered for the random selection of the washing machines to add to the columns of the matrix, $\mathbf{P}_e$.

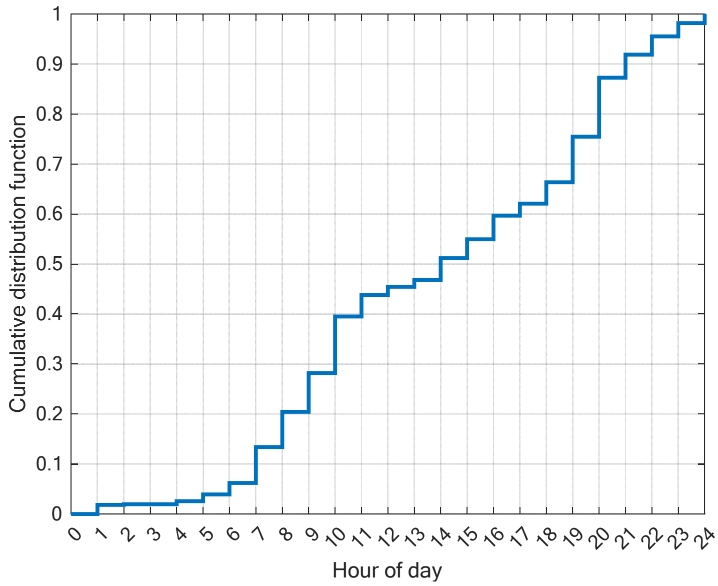


Figure 10. Statistical characterisation of the starting hours of the washing machines.

The Monte Carlo method has been executed by considering the termination criterion indicated in Appendix A with the threshold $\varepsilon = 5 \times 10^{-3}$, resulting in M = 3465 repetitions. Figure 11 plots the variation of the Monte Carlo test error for the increasing number of repetitions. An example of the total power required by the C_e washing machines for one Monte Carlo repetition is shown in Figure 12.

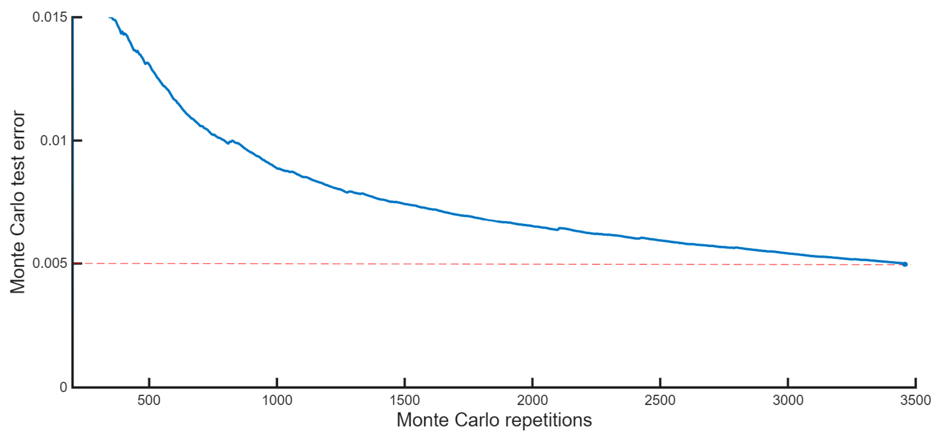


Figure 11. Evolution of the Monte Carlo test error until the termination condition. The red dashed line indicates the threshold.

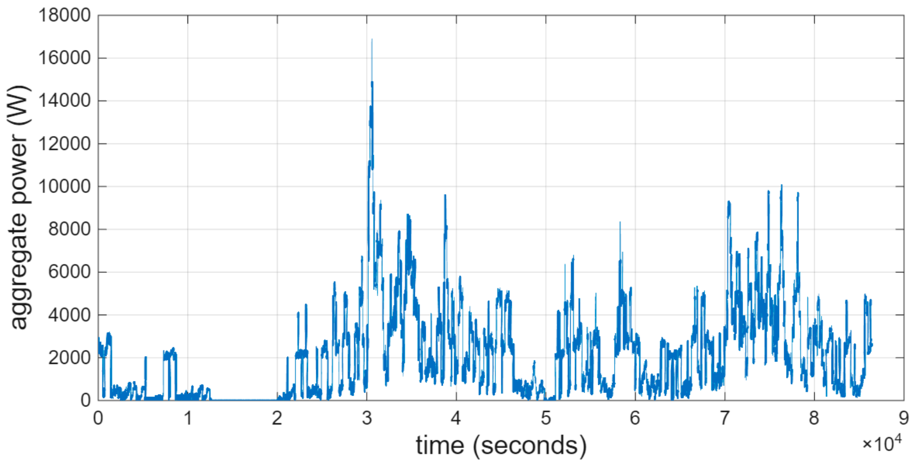


Figure 12. Daily power curve of the total power for one Monte Carlo repetition with a time step of 1 s (Case study 1—washing machines).

Then, the CDFs of the peak values and of two non-exceeding probabilities (for x% equal to 95% and 99%, i.e., at the 95th and 99th percentile) of the total power are shown in Figure 13. The results show to what extent the peak values have greater values with respect to the considered percentiles. In particular, the presence of a small number of relatively high and fast peaks is reflected in the tangible difference between the CDF of the peak power and the CDF of the 99th percentile.

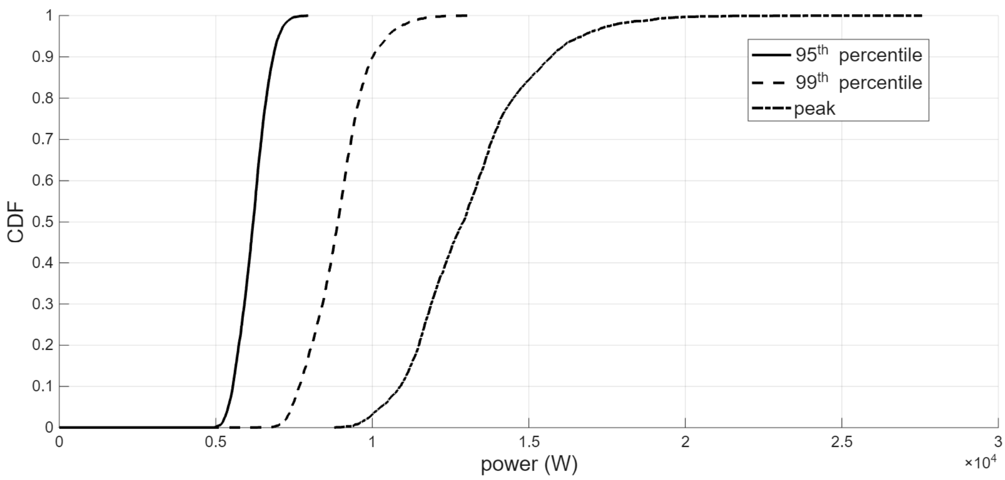


Figure 13. CDF of the peak values and of the 95th and 99th percentiles of the total power based on the Monte Carlo results (Case study 1—washing machines).

5.1.2. Reconstructed Load Patterns for Washing Machines

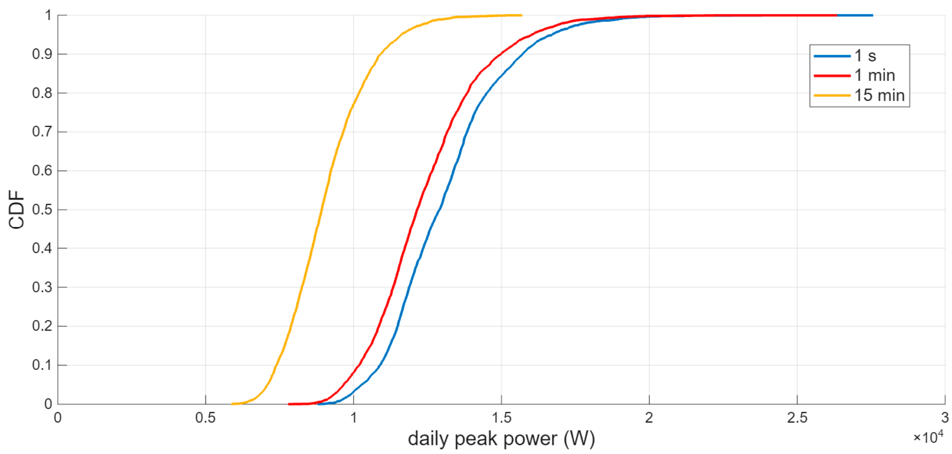
If the time step of analysis is increased, the immediate effect is to make the power curves smoother, losing some fluctuations that appear in the initial power curve. A specific analysis to show the variation of the indicators referring to the total power when the time step is increased has been performed. This analysis starts from representing the power curves for each appliance when the time step is longer than 1 s; in particular, two cases have been considered, with time steps of 1 min and of 15 min. The rationale of this choice is that 1 min has been found as a reasonable compromise between the dimension of the dataset and the representativeness of the shape of the power curves in earlier studies referring to distribution networks [38] and is also tested for the household appliances in this article, while 15 min is a typical time step used for metering purposes, as well for the definition of electricity market prices (since 1 October 2025, products with a 15 min Market Time Unit have become available for trading in the Italian Day-Ahead Market).

The same calculations carried out for the initial patterns at a 1 s time step have been executed with the 1 min and 15 min time steps. To be consistent with the data representation, in the Monte Carlo analysis, the choice of the starting instant of each appliance has been the same for all the time steps. In practice, during the execution of the Monte Carlo method for the time step of 1 s, the total power curves have also been determined for the time steps of 1 min and 15 min. For this reason, the stop criterion used for the Monte Carlo executions (described in Appendix A) is only the one referring to the 1 s time step, leading to M = 3465 repetitions.

Figure 14 compares the CDFs of peak values at the 99th and 95th percentiles of total power of the set of 200 washing machines with different time steps. The analysis reveals that when considering the peak power there are some differences between the CDFs at 1 s and 1 min time steps, due to the short-duration peaks that appear in the initial pattern at 1 s time step, which are mitigated in the averaging process that leads to the reconstructed patterns at 1 min time step. Conversely, at the 99th percentile and 95th percentile the CDFs at 1 s and 1 min time step are closer, as the effects of the peaks are less pronounced. The maximum values of the outcomes of the Monte Carlo method reported in Table 1 confirm the findings indicated above.

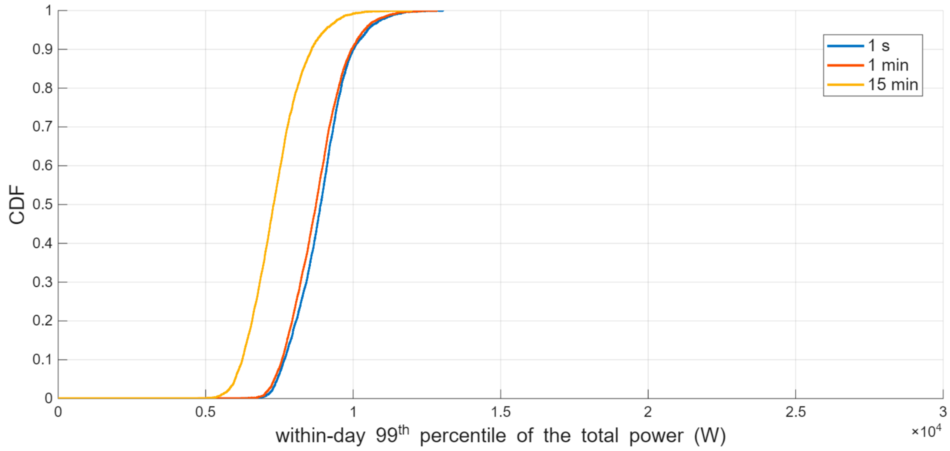
Table 1. Maximum values of the peak power at the 99th percentile and 95th percentile from the outcomes of the Monte Carlo method (Case study 1—washing machines).

Time Step	Peak Power (W)	99th Percentile (W)	95th Percentile (W)
1 s	27,562	18,966	16,706
1 min	26,341	18,104	16,019
15 min	15,701	13,043	11,618

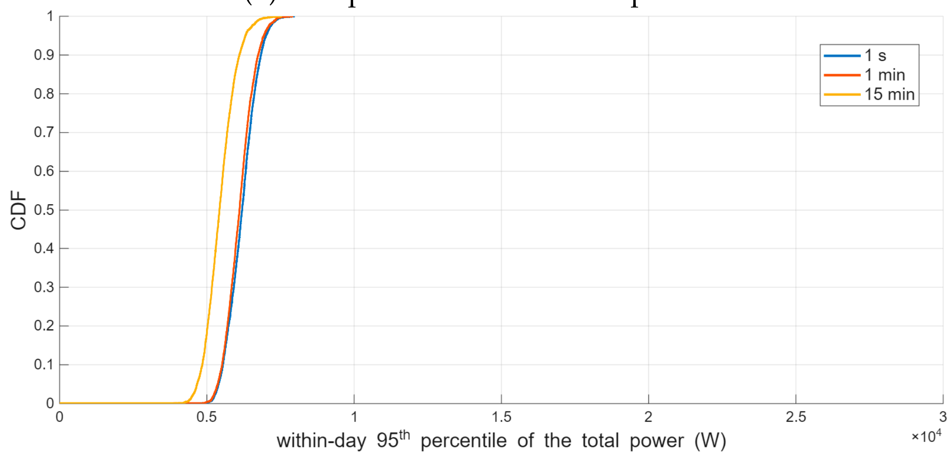


(**a**) Peak of the total power

Figure 14. *Cont.*



(**b**) 99th percentile of the total power



(**c**) 95th percentile of the total power

Figure 14. CDFs of the Monte Carlo outcomes of the total power (Case study 1—washing machines).

5.2. Case Study 2—Dishwashers

5.2.1. Initial Load Patterns for Dishwashers

This case study presents the results of the aggregate power curve of C_e = 200 dishwashers with a 1 s time step. The CDF of the starting hours of dishwashers is shown in Figure 15 based on the questionnaire responses from Italian respondents and for weekdays in the winter season. It is evident that the most frequent use is concentrated in the evening and after lunchtime. The power curves that describe the operation cycles of the available set of dishwashers (some examples are shown in Figure 5) have been considered for the random selection of the dishwashers to add to the columns of the matrix, $\mathbf{P}_e$.

The Monte Carlo method has been executed by considering the termination criterion indicated in Appendix A with the threshold $\varepsilon = 5 \times 10^{-3}$, resulting in M = 1680 repetitions. Figure 16 plots the variation of the Monte Carlo test error for the increasing number of repetitions. An example of the total power required by the C_e dishwashers for one Monte Carlo repetition is shown in Figure 17.

Moreover, the CDFs of the peak values and of two non-exceeding probabilities (for x% equal to 95% and 99%, i.e., at the 95th and 99th percentile) of the total power are shown in Figure 18. Although the power curves of the individual dishwashers have relatively flat portions close to the maximum power, when the power curves are aggregated, the values close to the peak value are reached only for a relatively short period of time, justifying the difference between the CDF of the peak power and the CDF of the 99th percentile (and in turn for the CDF of the 95th percentile).

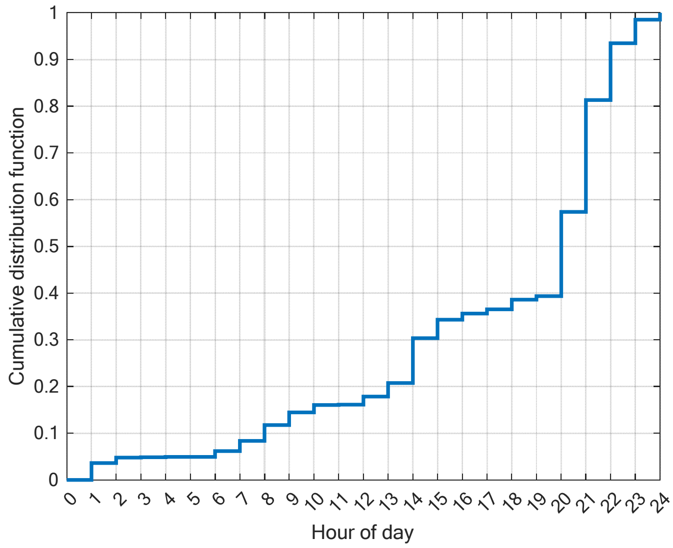


Figure 15. CDF of the starting hours for dishwashers.

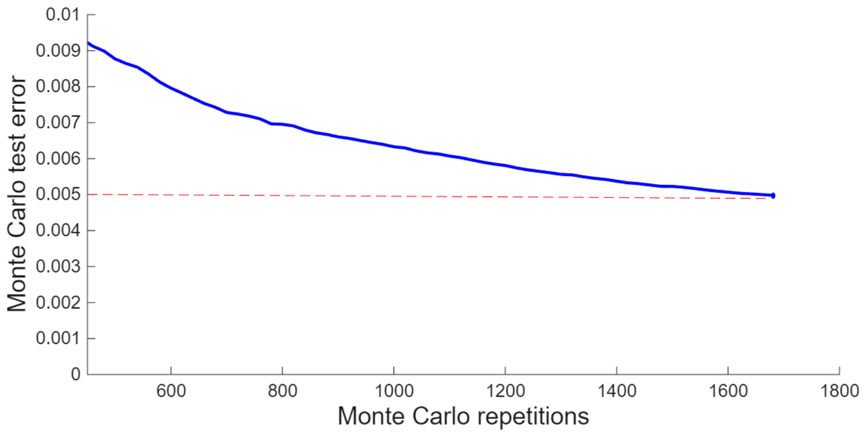


Figure 16. Evolution of the Monte Carlo test error until the termination condition (Case study 2—dishwashers). The red dashed line indicates the threshold.

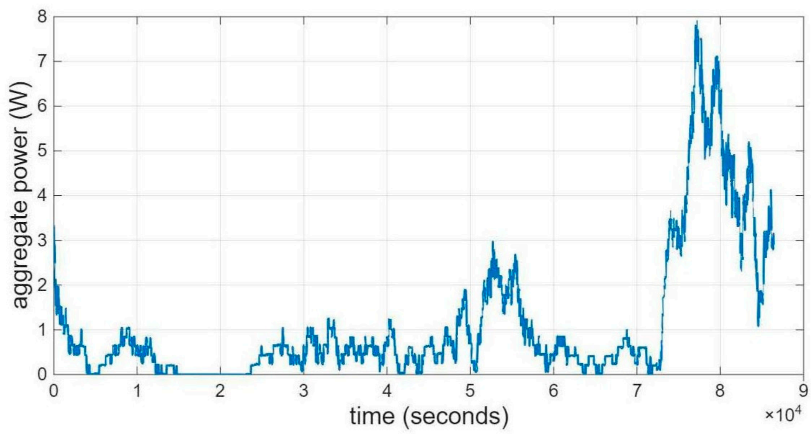


Figure 17. Daily power curve of the total power for one Monte Carlo repetition with a time step of 1 s (Case study 2—dishwashers).

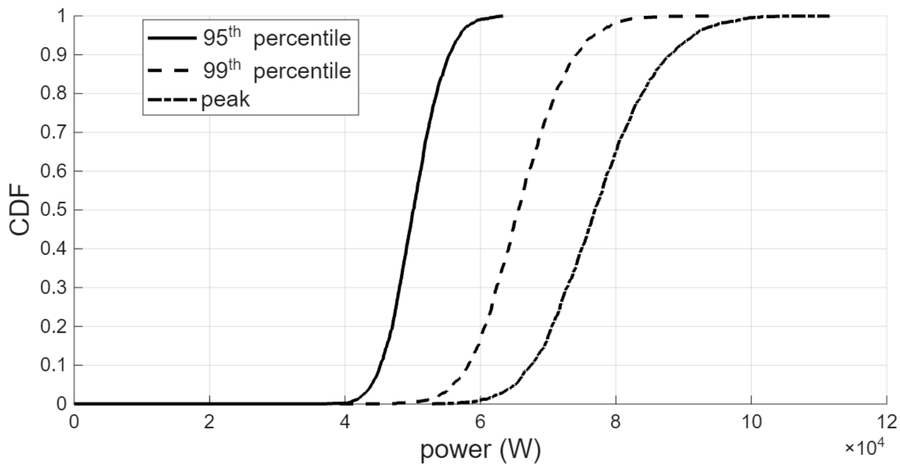
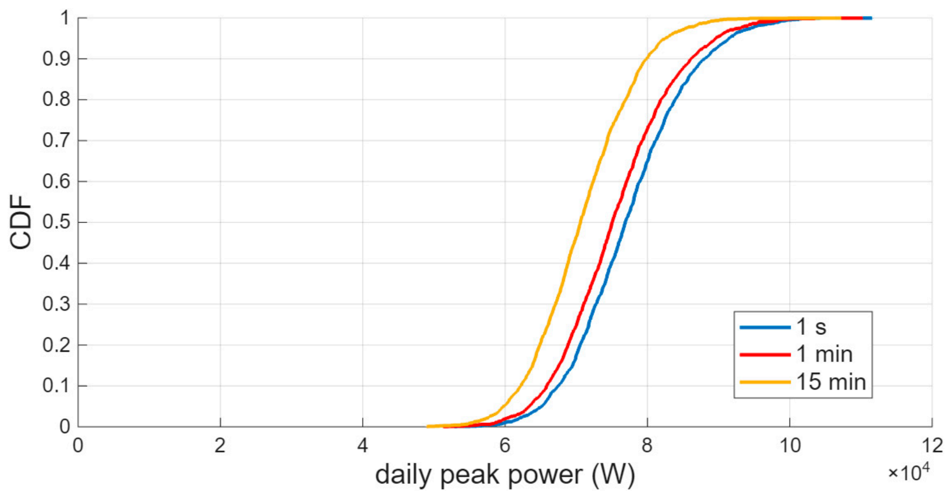


Figure 18. CDF of the peak values and of the 95th and 99th percentiles of the total power based on the Monte Carlo results (Case study 2—dishwashers).

5.2.2. Reconstructed Load Patterns for Dishwashers

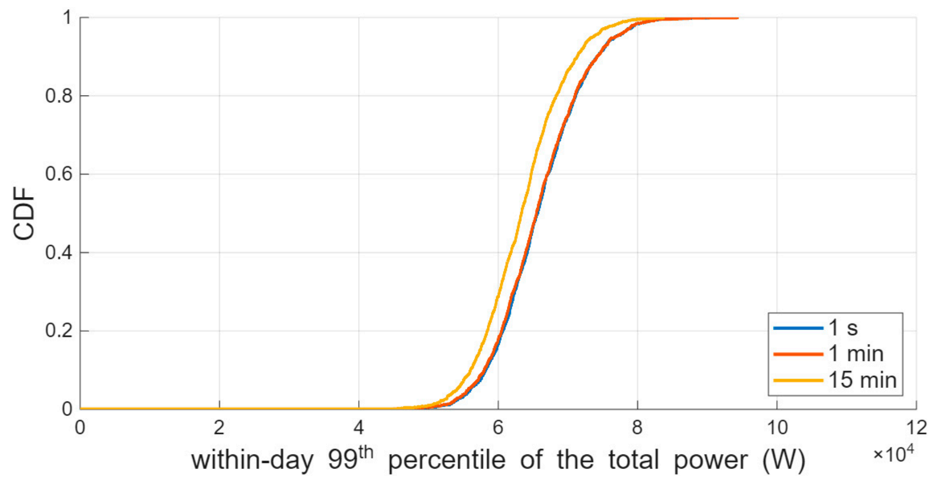
Also in this case, starting from the representation of the power curves for each appliance at 1 s, the load patterns have been reconstructed at time steps of 1 min and 15 min. Likewise, the calculations carried out for the initial patterns at the 1 s time step have been repeated with 1 min and 15 min time steps, with the Monte Carlo analysis, determining the power curves with the same termination criterion used for the 1 s time step that resulted in $M = 1680$ repetitions.

Figure 19 compares the CDFs of peak values at the 99th and 95th percentiles of total power of the set of 200 dishwashers with the different time steps. Differently with respect to the washing machines, the power curves of the dishwashers remain close to the maximum power for longer times, so that in the aggregation, the CDFs at time steps of 1 s, 1 min and 15 min are closer to each other. Therefore, the differences among the CDFs for the peak at the 99th percentile and 95th percentile of the total power remain relatively low, as confirmed from the results shown in Table 2.

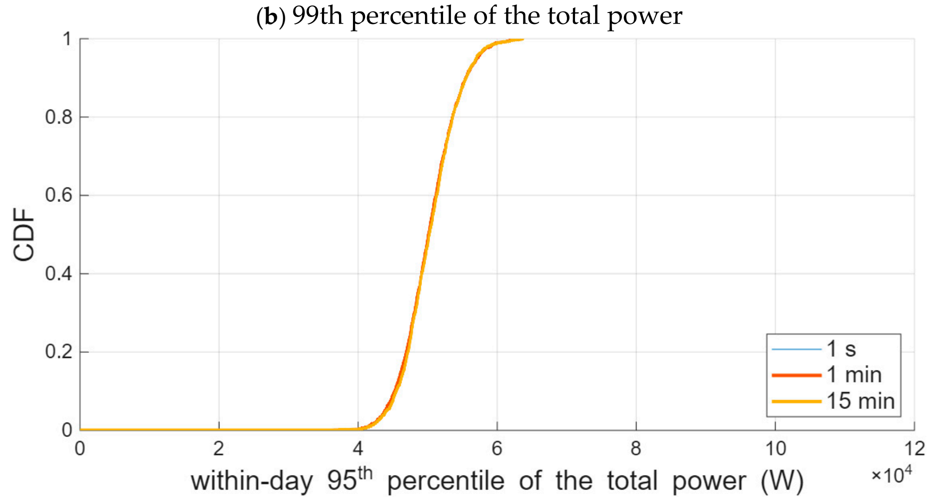


(**a**) Peak of the total power

Figure 19. *Cont.*



(**b**) 99th percentile of the total power



(**c**) 95th percentile of the total power

Figure 19. CDFs of the Monte Carlo outcomes of the total power (Case study 2—dishwashers).

Table 2. Maximum values of the peak power at the 99th percentile and 95th percentile from the outcomes of the Monte Carlo method (Case study 2—dishwashers).

Time Step	Peak Power (W)	99th Percentile (W)	95th Percentile (W)
1 s	111,553	98,409	91,489
1 min	110,233	95,623	89,553
15 min	107,220	88,661	82,464

6. Discussion

The combination of technical and user-based information is beneficial to form aggregate load patterns of the same type of household appliances. Since the users are generally less likely to respond to long and articulated questionnaires, the starting time of usage of the appliances is a single type of and effective information that enables the formation of a statistical input to be used in a bottom–up approach for reconstructing the load pattern of an aggregation of main individual appliances. The random extraction of the starting time from the probability distributions found from the questionnaire, associated with the random extraction of the power curve from a database of the appliance considered, provides useful insights on the actual usage of the appliance, obtaining the mean value and standard deviation of the load pattern of aggregated users over time.

Using data from real appliances, different operating modes of the appliances during real operation cycles are embedded in the power curve. Furthermore, possible effects of aging of the appliances are implicitly introduced by the fact that the real appliances monitored have been installed in different periods and have been used in different ways in the past.

In demand response studies, it is important to identify the power curves of the aggregation of household appliances of the same type for setting up targeted incentives. In future systems, a subset of users could expect to receive indications to change the starting time of individual appliances with manual control, for example, on a smartphone, associated with dedicated incentives, making it possible to increase the flexibility of the overall power curve. Even more, some users could expect to leave the command of some individual appliances to home management systems that execute optimisations based on electricity prices and availability of the resources.

Even in the prospect of highly automated management of electrical appliances in households, asking the opinion of the users about their usage of household appliances remains crucial, as not every user may be interested in contributing to the provision of more flexibility to modify the overall residential power pattern.

6.1. Enabled Aspects

In more detail, some significant aspects linked to the results obtained with the proposed approach are as follows:

(1) *Shifting in time* of some parts of the aggregated power curves found for the main appliances: Aggregate power curves assist operators in the estimation of electricity usage, at the same time quantifying the controllable resources that can become available at different times. Shifting in time, the power curves of a user can be driven by external signals targeted to a set of appliances or to an individual appliance. The management of such a situation requires the presence of an external entity with the function of an aggregator, which elaborates the information and sends command signals to the selected appliances. Moreover, and most importantly, only the users that agree to receive the signals can participate in the time-shifting process, with two possibilities: (i) the user receives an indication to change (e.g., defer in time) the operation of the appliance on a computer or smartphone, or (ii) the user enables the aggregator to directly send the commands. The latter solution requires suitable communication systems with the appliances, including input ports to receive the command signals, internal diagnostics, and output ports to dialogue with the aggregator, and its feasibility is conditioned by the impact of the introduction of advanced solutions in the appliance market.

(2) *Application of time-varying electricity prices*: The electricity price, together with economic compensations and benefits, is a major driver for shifting in time the power pattern, even in the absence of an aggregator. However, an effective communication system must be available to follow the evolution of electricity prices and send the relevant information to the users.

(3) *Participation in demand response programmes*: When considering a demand response framework, it is crucial to figure out two main aspects: (i) What is the present behaviour of users for various types of appliances? And (ii) what are the possibilities to shift the consumption to different times for different appliances? The contents of this article address the first point, providing evidence of the user's behaviour based on the direct responses of the users. To deal with the second point, a further survey would be needed, in which the users are asked about the acceptable delay time as the maximum time interval for which the user would anticipate or postpone the operation of an appliance without violating the user's comfort constraints. In this context, the appliances of major interest are the deferrable ones with substantial power

contribution to the demand curve. In a classical view, besides washing machines and dishwashers, the electric oven, iron, dryer and vacuum cleaner can be investigated with higher priority, followed by air conditioners and electric water heaters with user-defined activation. On a wider perspective, a massive adoption of connections of electric vehicles to a wallbox would drastically change the scenario, also requesting upgrades of the contract power of the users. Overall, the interaction with local generation (e.g., of the photovoltaic type) can drive the need for deferring the usage of appliances to periods of local generation. Finally, the possible presence of battery storage (e.g., shared between users, or energy community-based) would require a dedicated approach to manage the appliances in the households within the energy system for reaching specific technical, economic, environmental and social objectives.

(4) *Interactions with thermostat-controlled loads*: Many systems for heating/cooling are thermostat-controlled, so that they do not require direct start from the user's operations and do not belong directly to the category of deferrable appliances addressed in this article. For thermostat-controlled systems, the action of the users refers to the change in the temperature setpoint (manual or programmable). In this case, the thermostat-controlled appliances are connected permanently, the power pattern depends on the past history, and there is no starting time to be considered. For these reasons, thermostat-controlled appliances have not been considered in the proposed framework aimed at addressing an aggregation of shiftable appliances with user-based activation.

(5) *Interactions between the users and local energy generation systems*: Since the relevant variable at the point of connection between the supplier and the user is the net power (i.e., local demand minus local generation) in a local system without storage (still too expensive in many cases) matching the local generation by introducing changes in the local demand may be a viable objective. Which appliance can be shifted in time, and to what extent can be assessed by a home management system, also considering the uncertainty of the local generation and the willingness of the users.

(6) *Integration of electrical–gas energy systems*: Gas supply can be considered as an alternative to electricity at the design stage (choosing the type of supply, for example, for an oven or a water heater) or at the operating stage (when there is electricity–gas supply redundancy from integrated networks [39] for performing the same task (e.g., cooking), and the user can choose the type of supply. In the operation case, the information on the starting time of the electrical appliances has to be complemented by further information on the availability of an alternative supply system and willingness to use it instead of the electricity supply system.

6.2. Limitations

The proposed framework provides a complete approach from user-based information to the exploitation of measured data in a statistics-based context. The main limitations refer to different points:

(a) *Survey-dependent aspects*: The survey results depend on the number of respondents, types of areas of the respondents (i.e., urban, extra-urban and rural), number of occupants in the household and other family-related inputs, quality of the responses, periods of the year, and so forth. Information on the periods of the year are available with similar error margins and have not been included here for space reasons and because the methodology to be applied is exactly the same. However, if the set of respondents is reduced, the error margin referring to the reduced set increases and could become no longer acceptable when the set of respondents becomes smaller. To increase the significance of the results for more detailed groups of respondents, the questionnaire can be sent to an extended number of users. Moreover, as in any survey, there is a potential bias from the self-reporting of the users, which has been mitigated by an accurate check of all responses to filter out all the presumably inconsistent outcomes.

(b) *Database of appliances*: The appliances considered refer to a given database or to a set of measured units. There are limits in the number of appliances available and in the determination of the operation cycles or programmes. Furthermore, the representativeness of the appliances depends on the country, with the specific availability of appliances in the market and the electrification level (with differences in the typical contract power in various countries that impacts the type and size of some appliances used).

(c) *Variability in the daily usage of the appliances*: The users can start some appliances more times in a day or use the appliances only in some days of the week or month. If this information is available from the survey, the number of appliances considered in the aggregation can vary depending on the average number of uses in weekdays or weekend days.

(d) *Applications of the results*: Considering all the household appliances with user-based activation together, the results can be combined by following the same procedure, summing up all contributions of the individual types of appliances to the power curve. The outcomes are useful for a demand response study in which the focus is on deferrable appliances to address traditional demand-side management mechanisms of peak shaving and valley filling. However, appliances with user-based activation are not the totality of household appliances and cannot be considered alone in a grid-based study. To obtain results on the demand side that can be of interest for the grid, the power curves of all the appliances in a household must be merged into a power curve of the overall residential demand, adding the aggregated contribution of other types of appliances (e.g., refrigerators, lighting, etc.) estimated from different kinds of analyses outside the scope of this article.

7. Conclusions

This article has addressed some specific challenges in the development of reliable residential load models. Even though the availability of data referring to the usage of electricity is increasing due to advances in metering and communication technologies, the extreme variability of users' lifestyles still makes the electricity demand from household appliances highly unpredictable.

The results of a specific survey, based on a questionnaire sent to users to receive information on the starting time of usage of main household appliances with user-based activation, have related the household appliance usage to users' lifestyle. On these bases, the proposed framework has provided statistics referring to the total power of an aggregation of individual household appliances. This information is crucial to assess the impact of the demand from a given type of household appliance on the overall demand pattern of aggregate households.

The comparison among time steps of 1 s, 1 min and 15 min also shows that 1 min is a reasonable time step for preserving the representativeness of the load curve of the appliance without the need of using a very high number of points.

Being able to assess the probability of occurrence of a certain condition, e.g., the peak power or a given percentile of the total power at a specific time, can allow service companies to make various types of evaluations and establish demand response programmes with economic compensation and benefits for users willing to change the timing of their consumption.

The results presented in this article consider two main appliances. The methodology is ready to be replicated for other appliances, provided that enough data are available. The focus on the same type of appliance used in this article enables operators to study specific solutions to exploit possible time-shifting capabilities of the appliance to change the shape of the aggregate power pattern. This requires further information about the willingness of the users to accept requests for changing the starting time of the appliances, which has to come from a further survey that asks for users' opinions about adjusting the starting time, which is also based on possible incentives that can be applied in a demand response programme. Work is in progress to develop business models that incorporate the knowledge gained from the results illustrated in this article, with further findings related to social aspects and economics.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Determination of the Maximum Number of Monte Carlo Repetitions

The number of Monte Carlo repetitions needed to obtain statistically significant outcomes is generally considered to be high and in many applications is set out to a user-selected value. However, a more meaningful and statistics-based criterion can be applied to establish when to stop the Monte Carlo repetitions [40], as indicated below.

Let us denote as $\mathbf{r}$ the random variable under consideration. The sample mean, $\mathbb{E}_M\{\mathbf{r}\}$, and the sample variance, $\sigma_M^2(\mathbf{r})$, after M Monte Carlo repetitions, can be calculated by progressively updating, in an incremental way, the entries obtained after the previous repetition, as follows:

$$\mathbb{E}_M\{\mathbf{r}\} = \mathbb{E}_{M-1}\{\mathbf{r}\} + \frac{\mathbf{r}_M - \mathbb{E}_{M-1}\{\mathbf{r}\}}{M} \tag{A1}$$

$$\sigma_M^2(\mathbf{r}) = \left(1 - \frac{1}{M-1}\right)\sigma_{M-1}^2(\mathbf{r}) + M(\mathbb{E}_M\{\mathbf{r}\} - \mathbb{E}_{M-1}\{\mathbf{r}\})^2 \tag{A2}$$

where at the first repetition, the initial sample mean is equal to the extracted value, and the sample variance is null.

The uncertainty on the estimation of the random variable is characterised by the variance of the expected value:

$$\sigma_M^2(\mathbb{E}_M\{\mathbf{r}\}) = \frac{\sigma_M^2(\mathbf{r})}{M} \tag{A3}$$

The dimensionless expression used to identify the stop criterion for the Monte Carlo repetitions is the coefficient of variation, calculated as the ratio between the variance of the expected value and the expected value after M Monte Carlo repetitions, as

$$\beta_M = \frac{\sigma_M(\mathbb{E}_M\{\mathbf{r}\})}{\mathbb{E}_M\{\mathbf{r}\}} = \frac{\sigma_M(\mathbf{r})}{\mathbb{E}_M\{\mathbf{r}\}\sqrt{M}} \tag{A4}$$

The coefficient of variation can be considered as the Monte Carlo test error. More generally, if the z-score, z, is introduced to take into account a given confidence interval (e.g., z = 1.96 for a classical assessment of the 95% confidence interval), the Monte Carlo test error is changed to $z\,\beta_M$, and the condition for stopping the Monte Carlo repetitions occurs at the first value of M for which the Monte Carlo test error becomes lower than a user-defined threshold, ε, namely [41]:

$$\frac{z\,\sigma_M(\mathbf{r})}{\mathbb{E}_M\{\mathbf{r}\}\sqrt{M}} < \varepsilon \tag{A5}$$

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