Modeling and Aggregation of Electric Water Heaters for the Development of Demand Response Using Grey Box Models

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Abstract: Residential segments are of the greatest interest from the point of view of Demand-Side Resources and Decarbonization. Main end-uses such as water heaters, heating, and cooling have interesting opportunities: first, they can store energy, and this is relevant for the integration of renewables. Second, they are candidates for efficiency and electrification, increasing their demand share and the flexibility of demand. This paper aims to formulate an elemental Physical-Based Heat Pump Water Heater model that will enable the use of these energy-efficient appliances through aggregation in complex products, considering the advantages for demand and supply sides. Simulation results show that the individual performance is quite accurate and that the proposed model is flexible enough to be used to take more profit from energy markets or to easily respond to fast-occurring events. The model can be easily aggregated and used to obtain baselines, an important point for Demand Response evaluation. Results also demonstrate that demand–supply coordination and balance can be improved using these models to reduce or mitigate the risks and volatility of renewables without inducing a noticeable loss of service. Consequently, the contribution of this responsive load can be modelled through this methodology, making the engagement of more customer segments in Demand Response policies more credible and deploying new segments, such as prosumers.

Keywords: demand response; energy efficiency; heat pumps; physical-based load modelling; aggregation; energy balance; distributed energy resources

1. Introduction

During the last two decades, developed countries have increased the participation of Demand Response (DR) beyond Energy markets, for example, through the participation in Capacity and Ancillary Services markets. Even with all its relative success over these last years (between 2% and 6% of peak demand), DR has been considered a standalone resource, basically valuable for large-demand customers. This is especially true from the point of view of supply-side agents, which consider the management of large-demand segments cheaper, easier, and more reliable.
Kyoto and Paris agreements have changed the energy policy of several countries during the last decades. For instance, decarbonizing our society in the next two decades will involve a dramatic change in energy conversion and demand [1]. This scenario requires the change from gas and fossil fuels to electricity and renewable sources (RES), but the increase in demand requires efficiency and, perhaps, the change of usage patterns to better align demand with renewable outputs (for example, Photovoltaics) and system requirements (e.g., increasing the hosting capacity at distribution levels) taking profit through synergies with other resources, such as battery storage. First, electricity should play a more important role in the future through electrification (especially in heating/cooling and water heating end-uses). Residential sectors should gain interest because they explain 30–35% of the overall demand and a similar share in emissions (up to 10–15% of GHG emissions in some countries [2]). Second, the energy mix will experience a revolution that benefits the penetration of renewables (RES) both at low (prosumers) and large scale, but renewable generation and residential demand are not synchronized most of the time. Third, due to this growth in RES, several states in the US, EU, and other countries have experienced frequent periods of overproduction in the Power System. This means that non-dispatchable base-load generation and RES have exceeded demand during some periods, resulting in the curtailment of RES or negative prices in energy markets. This can be observed in the European Power Exchange, EPEXSPOT market [3] since 2018; for instance, prices in the EPEX SPOT market (Belgium) reached −€115.31/MWh in April 2020. Escalating prices of gas, decommissioning of carbon power plants, and an increase in the cost of CO2 emissions, as well as a lack of responsive resources in the system, can explain this scenario; consequently, a lack of elasticity of demand contributes to price volatility.

This paper proposes a physical-based model for Water Heaters (WH) and a methodology that takes advantage of flexible loads to better integrate Distributed Energy Resources (DER) into residential segments. The methodology can and should interact with other tools such as Non-Intrusive Load Monitoring (NIALM), load segmentation, and Customer Baseline Loads (CBL) methodologies to face main DR problems and improve DER characteristics to participate in complex products and services in the coming years. The main contributions of this paper can be summarized as follows.

The paper presents a model to improve the knowledge of Heat Pump Water Heaters (HPWH) dynamics (in the short and very short terms, relevant to use in Ancillary Services and Markets) through the consideration of Physical-Based Load Models (PBLM) methodologies. PBLM can also be used by aggregators to evaluate the potential and response of other main end-uses at residential and commercial levels: electric heaters (EH), electric thermal storage (ETS), heat pumps (HP), and water heaters (WH). This approach outperforms practical models, especially when new response policies, weather, or use changes appear. Basically, this is due to a lack of previous experience and available data arising from the use of other models.

The proposed model gives feedback about the different temperatures of the water near the indoor sensors that return information to thermostats that drive the switching of compressors and ancillary resistors. This is important because the location of sensors is not always the same, and other models in the literature consider only one or two temperatures, which can cause errors in demand patterns, especially when DR is applied. Obviously, the model reports the temperature of hot water draws to check an appropriate customer service level during DR.

Also, the model can provide end-use baselines (improving the definition of the overall baseline CBL) according to weather and water use habits and can evaluate demand despite the lack of measurements in specific DR conditions. This is a consequence of its grey-box structure.

The methodology can take advantage of feedback and synergies from other potential tools used by aggregators or utilities (e.g., load clustering, NIALM, short-term load forecasting, and renewable forecasting).
The rest of the paper is organized as follows. Section 2 depicts the characteristics of WH in different countries and the possibilities that arise for residential Electric Water Heater (EWH) loads in DR programs. Section 3 deals with the literature review of EWH load models and DR programs, focusing on residential DR programs. In Section 4, the methodology to define the elemental PBLM and the different tests used for the model definition and validation are stated. This includes practical considerations to achieve greater flexibility of the proposed PBLM model in new and complex products (e.g., in ancillary services). Section 5 outlines the segmentation and aggregation procedures to define groups of loads suitable to get an ensemble of loads that can participate in DR policies with accurate surveillance of customer comfort, according to the characteristics of the elemental model (and real loads) defined in Section 5. Section 6 presents some simulation results of the model in two scenarios: peak shaving and the change of storage pattern to follow renewable generation. Some advantages and practical limitations of models and loads are discussed. Finally, the main findings and recommendations of the study are presented in Section 7.

2. Demand Response and Residential Customer Segments

According to the US Federal Energy Regulatory Commission, DR programs have the potential to reduce around 32.9 GW in the US Electric Power System (2023), but only around 11 GW were deployed in 2022 [4], which represents 6.5% of peak demand (a slight decrease from 2011 due to the increase of the overall demand). The residential sector accounted for 8.8 GW of 32.9 GW, but only 29% of resources were deployed.

WHs have been well-suited loads for DR for decades, and customers are aware of their potential to reduce energy costs in, for instance, France and the US. Moreover, it is more difficult when customers experience severe problems during control actions due to intrinsic energy storage available in these loads. The challenge for the coming years is to fully exploit EWH potential through the development of new and complex products beyond peak shaving options. This objective encompasses the development of thermal models to better predict demand, demand flexibility, and the dynamics of residential EWH, as well as the basis to further implement optimal and complex strategies, considering that the energy conversion technology will change from ERWH to HPWH.

2.1. Review of Domestic Heat Water Technologies and Trends

Most households in developed countries use natural gas for domestic water heating (DWH). For instance, 90% of households in California, according to [5], resulting in high GHG emissions. Energy and environmental agencies strongly recommend building electrification. For instance, GHG objectives are fixed around a 55% reduction by 2030 in the European Union [6] and an 80% reduction in California by 2050 [2]. Some data depicts the strong development of a new scenario for electrification through WH in recent years (2016–2019): ERWH has increased in France by 20% (from 12 to 14.7 million) and Spain (from 6.1 to 7.3 million). In Portugal and Greece, the number remained stable, whereas it decreased in Germany (from 4.4 to 1.9 million dwellings), but with a growth of Solar Thermal WH (SThWH). Secondary homes are also relevant to the evolution of end-use shares. The number of these homes is estimated to be 30 million in the EU (i.e., almost 12% of the overall number of dwellings). It can be expected that a significant share of these secondary homes will be equipped with ERWHs due to the lower investment costs of those appliances.

Specifically, energy agencies have recommended the adoption of HPWH technology or sometimes the increase of ERWH tank capacity, considering a conservative scenario for the adoption of HPWH by consumers, to begin before 2030, but this option increases electricity consumption.
An increase in HPWH adoption, advisable for energy efficiency (e.g., the new Energy Efficiency Directive EU/2023/1791 in the European Union) and environmental points of view, can be possible through the change from hydrofluorocarbons to new refrigerants. From a Global Warming Potential (GWP) indicator, we can change by around 1400 with actual hydrofluorocarbons to advanced HP with CO₂ (GWP 1), a possibility in some markets like Japan. Refrigerants (e.g., R-1234yf) with GWP 4 can reach COP around 3.0–3.5 for some units in mild climates by 2030–2050 [1]. Gains in efficiency clearly explain the expected rising trend of HPWH and, consequently, the interest of this load for the replacement of ERWH. The household location of HPWH is important from the point of view of efficiency because, depending on the location of HPWH inside the dwelling, the model of heating space should consider additional heat gains (internal loads). These considerations are not a problem with the proposed grey-box modelling methodology (PBLM) because both load models can be easily linked (see Section 4).

Besides, it is necessary to consider that when the external temperature drops or during high water demand periods, the internal control mechanism of HPWH switches from heat pump to electric resistor mode to achieve an increase in energy conversion (between 4–8% of working time, according to own laboratory tests). This involves a decrease in the overall efficiency of the unit; moreover, the load changes its dynamics. In this case, external control is justified from both the economic and technical points of view to manage appliance efficiency and energy rebounds after control signals. SThWHs are the likely alternative in the short term because they play an important role in mitigating demand and emissions, but SThWH is far from a broad application because capital costs remain of importance (€5000–€7000). Moreover, these systems need an ERWH or HPWH to support water demand if the primary resource fails, which justifies the interest in models for EWH management.

2.2. Deployment and Main Characteristics of EWHs

EWHs are as an interesting option for improving the future power system’s reliability, energy transactions, and environmental concerns. EWH was defined as a “hidden battery” a decade ago [6] because an EHW stores thermal energy, whereas its characteristics can help cover other missions, which is far from traditional DSM policies. Nevertheless, WHs engaged in DR pilots usually are large-size units, around 200 or 300 L, to cover needs for several end-uses (apart from personal care) and to take profit from Time of Use tariffs (ToU). This picture represents an equivalent “hidden” storage of around 2–5 kWh (considering 55–65 °C inside the water reservoir). Thus, EWHs can store energy as much as electric storage systems do, but with an increased lifetime (number of cycles) and a reduced capital cost, especially for ERWH. Nevertheless, environmental and efficiency subsidies by utilities and states could make HPWHs competitive. A main problem of proposed alternatives [2] is that some residential segments equipped with Gas WH (GWH, e.g., apartments or flats) do not have the possibility to install large EWH appliances, or they use hot water for human uses only, which limits the benefits of a larger tank. An additional problem appears when technology is changed from EWH or GWH to HPWH whose size is 20% greater and takes more time to heat water. From the authors’ point of view, future scenarios for WHs present several variants for different customer segments and countries (technologies, tank size, water use, etc.). Table 1 shows the distribution of ERWH in France according to WH capacity (note that data are from 2007, but they are still representative of the residential segment), the kind of WH, and primary energy used for heating.

From the point of view of control, EWHs may have unique competitive advantages with respect to other DERs: they are more uniformly distributed throughout the power system, and consequently, DR could potentially lead to larger benefits because they can be a more reliable resource through the distribution and transport levels.
(and the penetration of HPWH) can change DR missions for loads and the requirements of (mainly ERWH). The EU average is around 150 L, with the biggest sizes in France (258 L) (e.g., the evaluation of offline flexible resources).

The capacity of the tank is another important factor because it conditions the storage potential and the time of curtailment, and this can lead to a higher possibility for customer complaints. This capacity varies from country to country. In [11], the capacity of WH tanks is analyzed for EU countries. Figure 1 gives the average volume of larger (>30 L) EWH (mainly ERWH). The EU average is around 150 L, with the biggest sizes in France (258 L) and Finland (229 L). The smallest size corresponds to Italy and Spain (67–90 L). This size (and the penetration of HPWH) can change DR missions for loads and the requirements of models to better represent those policies.

The deployment of the Internet of Things has made two-way communication and control devices at home that provide necessary feedback to aggregators (smart thermostats and residential monitoring; e.g., CTA-2045 protocol [8]) cost-effective. For instance, a large amount of demand data with higher granularity can improve load forecasting. These smart and two-way devices can also give feedback about the status of the appliances involved in flexible groups for Demand Response and information about end-use service (e.g., the temperature inside the dwellings or water draw temperature in the simulation case proposed in the paper). This feedback can also benefit the development of more accurate demand baselines or improve the knowledge about the status of load response (e.g., the evaluation of offline flexible resources).

EWH (i.e., HPWH) or that building codes assume this technology for new or refur-

Finally, HPWH sales have increased drastically in the US and EU. For instance, France increased HPWH sales by 13% from 2018 to 2019 (116,000 appliances in 2019 vs. 103,000 in 2018) or 12% of overall WH appliances in 2019 (Table 1). This increase can also be explained by energy-efficiency policies in buildings [9], at the expense of GWHs and SThWHs, which have decreased in sales (between 5% and 20%, according to [10]). In California, incentive programs ($1000 to $3000) developed by some utilities and some interesting changes in building codes act as a catalyst for HPWH adoption.

Table 1. WH technologies in France (2019) and share of ERWH according to tank capacity ([7]).

<table>
<thead>
<tr>
<th>Type of WH</th>
<th>Share in 2019 (vs. 2016)</th>
<th>Volume (L)</th>
<th>Share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GWH (Gas)</td>
<td>24 (21)</td>
<td>80</td>
<td>5.5</td>
</tr>
<tr>
<td>STxWH</td>
<td>2 (1)</td>
<td>100</td>
<td>3.3</td>
</tr>
<tr>
<td>ERWH</td>
<td>51 (52)</td>
<td>200</td>
<td>60.5</td>
</tr>
<tr>
<td>HPWH</td>
<td>12 (2)</td>
<td>400</td>
<td>17.0</td>
</tr>
<tr>
<td>Rest</td>
<td>11 (3)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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Figure 1. Average storage volume of EWHs, per EU member state [11].
2.3. Potential DR Tasks for Electric Water Heaters

EWH appliances can be classified into three main subclasses: instantaneous (EIWH), resistance (ERWH), and heat pump (HPWH). Energy patterns and conversion are different in each one, and these characteristics explain their suitability to perform in different markets and services. EIWH are not considered in this work because they require a high demand for residential segments (around 10–12 kW); they do not suit well basic energy efficiency (EE) objectives; and their demand is concentrated in very short periods in the day, which limits the DR availability of those appliances.

Some authors consider that the attractiveness of the end-use loads to participate in DR programs is inversely proportional to load efficiency. This can be explained by the reduced demand; however, in the case of HPWH, this does not apply because (i) two sources of demand can participate (the compressor and the ancillary resistor) and (ii) they have an important energy storage potential without significant additional costs. Four ways of using EWHs as DR&EE resources can be analyzed, considering the relevance of small-sized EWHs in some countries (Figure 1). The main strategies considered for EWH are [12–14]:

- **Peak shaving (hourly basis):** The WH is controlled only on a limited number of days when the system peak is likely to occur (typically 10 to 15 days per season during 2 to 4 h [6]). This strategy is used to get revenue through Capacity Markets.
- **Thermal storage (daily basis):** Typically, the WH heats at night, and then heating is curtailed during the highest-priced hours of the day. This strategy depends on the size of the WH reservoir (i.e., it benefits larger units), and it has been very common in several countries through different types of ToU tariffs, including direct load management by utilities.
- **Fast response:** In this strategy, EWHs offer frequency regulation or services to System Operators (SO). Demand resources respond to SO signals (e.g., “regulation D” or “regulation A” signals in the PJM system in the US) and change their state (ON/OFF). Some of these fluctuations are energy neutral (e.g., regulation D) on an hourly basis, an interesting characteristic of thermal storage because it has a worse or limited performance when the temperature (HPWH) and demand are committed to continuously rise from baseline levels, apart from health concerns above 65 °C.
- **Energy efficiency:** This scenario assumes that customers invest in a more efficient EWH (i.e., HPWH) or that building codes assume this technology for new or refurbished buildings. In this case, the objective is basically to save energy and, secondarily, to get some capacity value from this change. The change in demand is not trivial because it does not depend only on a constant coefficient due to COP; COP changes when ambient and water temperatures do [12], which they can do.

All these strategies have usually been seen as exclusive by regulators and utilities because aggregation—for example, in Europe—faces important educational, legislative, and regulatory barriers (only 1 of 27 countries in Europe reported aggregation activity in 2022 in all energy markets [13]) but, in the future, customers and aggregators should integrate the development of complex DR products in the demand-side, the supply-side or both (e.g., the engagement of the “same DR actors” in several markets and services) due to legislative efforts worldwide [13]. For this task, it is necessary to develop a specific model for each duty, or the integration of several models, capable of providing the necessary feedback to properly perform on these new and complex scenarios.

2.4. Comparison between ERWH and HPWH for Modelling Purposes

The behavior of an elemental HPWH is quite different from the individual ERWH demand—even those of the same size, especially for small WHs. For example, the levels and duty cycles of demand (see switching frequency and amplitudes; Figure 2a). Moreover, in the case of HPWH the amplitude can change around 30–50%. The change of profiles in the aggregated demand curve is less significant than in the elemental one. Still, the rugged profile of ERWH is made clearer in the case of HPWH. Some delays appear (Figure 2b) due to the different dynamics of resistors and compressors and the different energy used for
water heating (e.g., 1200 W resistor vs. 300 W heat pump). Another problem is the number of HPWH required to reach the minimum level of response (a threshold ranging from 100 kW to 1 MW, depending on the specific country and Power System [13]). It becomes twice or threefold the number of ERWH, assuming a COP around 2.0–2.5 for small units. Consequently, a model that relies on COP and temperature must be considered for specific applications. This concern does not apply to ERWH.

![Image of individual and aggregated appliance demand curves: (a) Recordings for 80 L ERWH and 80 L HPWH; (b) Simulation of the average aggregated demand with DR control (40 WH loads with a standard water service profile in winter, granularity of the simulation output 15 min).](image)

Finally, the environmental impact is another concern. HPWHs contribute to the reduction of CO2 emissions due to their greater efficiency (from 1.6 to 3.5, according to the literature). Additionally, they can impact CO2 emissions through a change in demand patterns. When the load is shifted from peak hours to off-peak hours (renewable or power systems, according to the interests of each party), emissions change depending on the marginal generation technology being used in the mix during those hours (e.g., solar vs. gas).

For these reasons, a good DR model for these appliances must provide feedback on these concerns and, obviously, should make the evaluation of parameters and aggregating models easier.

### 3. Literature Review for Water Heating Modelling

Several works dealing with EWH modelling can be found in the literature. First papers dealing with the use of ERWH for DR introduced the so-called one-zone/mass model (i.e., one capacitor to model the storage capacity of water, or “1C”) to simulate the dynamic of water temperature inside the tank/reservoir using a first-order differential equation [14] or a stochastic first order-partial differential equation (SPDE) [15]. Ref. [14] develops the aggregation of ERWH using Monte Carlo methodologies, whereas [15] applies probability density functions obtained through the resolution of SPDE. This last approach considerably simplifies the aggregation process and reduces the simulation time. Models reflect the dynamics of water temperature assuming a uniform distribution of temperature into the reservoir, but this is not true because laboratory measurements (see Section 4) clearly state that some significant variations of the temperature appear through the tank (stratification) after most of the water draws (e.g., water draws around 10–20% of tank capacity) due to cooking, shower, or bath requirements. Consequently, the estimation of temperature and thermostat control are wrong.

In [16], a two-node/masses ERWH model (i.e., the use of two capacitors to model the storage capacity, or 2C) is developed. The model accounts for both thermal dynamics and users’ water consumption. The model assumes fixed volumes for the cold zone (bottom of the tank) and warm zone (top of the tank), and the temperature in each node is assumed to be uniform. Unfortunately, there is some lack of validation of the stratification with real data. Water draw patterns were estimated using average residential demand profiles.

Ref. [17] presents a hybrid model that changes between one and two masses/zones (1C to 2C) depending on the service of WHs. The authors use a first-order model to model
WH dynamics when the WH is charged or fully discharged (after a major water draw). The simulator remains with this model until a draw occurs, and it uses a model very close to [16]. The height (capacity) of the lower (cold) zone goes down when the appliance demands power to get the thermostat setpoint and remains with this model until the WH is fully charged. Then, it changes to a one-zone model. The author’s simulation results show the effectiveness of WH responses and their dependence on hot water usage with this hybrid model. The main problem is that the model is not tested against measured data to make a comparison of its performance possible.

Through a partial differential equation, a physical-based model is developed in [18] to describe the temperature profiles at different WH tank locations. The WH has two resistors that operate independently. Sensors are located at different positions, and the model allows us to know the temperatures at each site and evaluate the ON/OFF state of each resistor. The model was validated against field test data for more than 10 days. The validation scenario is quite limited because only four water draws were tested. Another main drawback is that the computational complexity is like [15] but significantly higher than in the cases of the one- or two-node models [14,16,17]. In DR scenarios, the simulation time is very relevant because WHs need a further aggregation process, and such a model requires an excessive amount of time to obtain results to be useful for aggregators in some services or markets—for instance, in Ancillary Services (AS).

The physical model presented in [19] divides a large WH tank into eight zones/masses (8C) to develop a more complex model to account for water stratification. The simulated response of the joint model represents the measurement data quite accurately. The problem is again the limited scenario used for validation: 70 h without any draw and then a constant water demand for 2 h. Other significant scenarios, such as the charge/discharge of WH or several draws at different water demands, are not considered. The main problem is whether the inherent complexity of considering eight zones (or more) in the tank is justified to define the dynamic of sensors that drive thermostats.

Ref. [20] presents a model for ERWHs with a horizontal tank. The model intends to be unlimited with respect to this kind of WH and computationally inexpensive in resources in smartphone applications. Regarding vertical WH, the thermocline changes its overall surface (i.e., the border area between cold and warm zones/masses in the horizontal WH). This problem causes failures in most of the models being presented in the literature. The authors performed simulation and validation during 53 days with 103 events (water draws), and the model exhibited good performance and speed. Aggregation is not considered in this work. The authors suppose that all converted energy by resistors is transferred to the lower (cold) node, but this is not true in all WHs. This hypothesis will change the behavior and response of HPWHs.

On the other side, Ref. [21] depicts a hybrid technology alternative for DWH. The proposal integrates an instantaneous electric shower EIWH and an HPWH powered by a renewable system. The hybrid system reduces the possibility of events without warm water in the house but limits the efficiency of the overall DHW system and increases the power input for this end use due to the high demand for the instantaneous shower appliance. The authors assume that the temperature of the water through the tank is constant. The consideration of a tank without stratification can affect the results because the temperature drives the thermostats and its demand, as discussed in [18,20].

A high-resolution multi-energy model is proposed in [22] to estimate residential dwelling energy demand. Models for space heating are physically based, but for DWH, only appliance profiles are defined and integrated into the overall heat demand of the household. The dynamics of the WHs are not explained or considered. A tank with a homogeneous temperature (without stratification) is proposed. It interacts as a thermal input on space heating models.

In [23], the authors present an elemental and an aggregated model for the Australian Power System that intends to switch from low to high renewable sources periods. The authors use a one-mass model based on [14] and identify parameters at a nation-wide scale.
Validations do not respond to habitual working scenarios (thermostat dead-bands between 10 and 20 °C, size of the reservoir from 100 to 300 L), and all electrical parameters are assumed to be the same without considering any statistical distribution in the aggregated load, which does not seem an actual scenario for a nation-wide system.

4. Methodology

DR policies involve the development of several tasks, including planning, operation, measurement, and verification. Usually, performing each task requires the use of some specific methodologies, but this becomes very complex, especially if the aggregator must manage several customers with specific characteristics in different markets and services. Thus, the aggregator’s work can reach considerable complexity in most cases due to the use of specific models for each scenario and customer. The authors propose using a limited set of interlocked methodologies, which may help develop different DR tasks. In this sense, the option uses a detailed knowledge of underlying physics, the engineering principles of service provided by loads, and the consideration of mathematic tools that can explain results and facilitate the simulation.

4.1. PBLM Models

PBLM models consider the physical laws of the loads and their environment to determine the behavior and changes in the appliance-environment system. The model defines an energy balance between heat gains and losses, heat generation, considering the storage capacity, and heat leakages (water flows). The control inputs of the model are changes in the setpoint of the thermostats, input/output water, or the control applied to the electricity supply. All these variables account for the service and state of the load at any time. The model needs to be tuned and validated through real submetering measurements or NIALM, including the response of the load to control strategies or other DR policies.

According to the required flexibility for the load response (energy, balance, and ancillary services), the location of temperature sensors, and the size of the tank (80–100 L), the proposed HPWH model is a thermal-electrical equivalent model with three masses/zones or 3R3C (to reproduce heat losses and storage of the overall model [24,25]). The model includes two heat (current) sources: the heat pump (main heat source) and the auxiliary resistor. Figure 3 depicts the HPWH model and its interaction with the environment (Xp, the temperature of the pipeline, andXd, the temperature inside the dwelling).

![Figure 3. Thermal-Electric equivalent of PBLM for an elemental HPWH load.](image)

The capacity of the tank is divided into three zones to better represent the water stratification and its effect near temperature sensors without increasing the complexity of the model (Section 3). The three zones are the hot-water zone, WH1 (water outlet); the mixed zone, WH2; and the cold-water zone, WH3 (water inlet; Figure 3). The stratification effect is a phenomenon in which the hot water inside the tank raises to the top of the
reservoir while the cold water remains down to the bottom after a draw occurs with a limited mix of flows in the short-term.

The main features (and parameters) included in the model are:

- **Heat gains**: Two heat sources, the heat pump (\(H_{HP}\)) and the auxiliary resistor (\(H_R\)).
- **Heat storage**: From the specific heat of water inside each of three masses/zones being considered (Figure 3): \(C_1\), (hot-water zone), \(C_2\) (mixed zone), and \(C_3\) (cold-water zone). This storage capacity depends on the tank size for each zone (WH1-WH2-WH3) and the specific heat of water (\(C_e\)).
- **Heat losses**: Through the tank envelope (\(G_{Ex}\)), through the pipelines (\(G_{Cx}\)), and the heat losses in the exchange layer between the three zones of the tank (\(G_L\)) (where \(x = 1, 2, 3\)).
- **Water flows**: Water flows are represented by dependent current sources (\(C_e q(t) X_x(t)\)), where \(q(t)\) is the flow extracted from the reservoir; at a specific water temperature, the flow extracted from the reservoir represents the service that customers obtain and require from this end-use).
- **Intrusive or non-intrusive control mechanisms**: represented by smart thermostats or direct ON/OFF control of supply (compressor or resistors that independently drive \(m_{HP}(t)\) and \(m_R(t)\) switches, Figure 3).
- **State variables**: they are the temperatures inside the tank, represented by the temperature in each zone of the tank/reservoir (hot/mixed/cold; i.e., \(X_1, X_2, X_3\)).
- **System inputs**: The temperature of the dwelling in which the load is located (\(X_d\)), the temperature of the inlet water, (\(X_p\)), and water flow \(q(t)\), which also determines energy flows.

The state-space system for the model in Figure 3 is

\[
\begin{pmatrix}
\dot{X}_1 \\
\dot{X}_2 \\
\dot{X}_3
\end{pmatrix} = 
\begin{pmatrix}
-G_{L1} + G_{C1} + G_{E1} + \alpha C_e q/C_1 & \frac{G_{L1} + \beta C_e q/C_1}{C_1} & 0 \\
0 & -(G_{L1} + G_{L2} + G_{E2} + C_e q)/C_2 & 0 \\
\frac{G_{E1}/C_1}{C_2} & 0 & \theta_1/C_1 \\
\frac{G_{E2}/C_2}{C_3} & 0 & \theta_2/C_2 \\
\frac{G_{E3}/C_3}{C_e q/C_3} & \theta_3/C_3 & \theta_3/C_3
\end{pmatrix} 
\begin{pmatrix}
X_1 \\
X_2 \\
X_3
\end{pmatrix}
\]

where \(D\) is the differential operator (\(d/dt\)), \(\theta_1, \theta_2, \) and \(\theta_3\) represent the fraction of the total heat supplied by energy conversion devices to each zone into the water tank (hot/mixed/cold). Moreover, \(\alpha\) and \(\beta\) are the fraction of the outlet water that comes from each zone of the tank, basically zones WH1 and WH2 (the water outlet of WHs usually is at this zone) at \(X_1\) and \(X_2\) temperatures, respectively (because there is some mix of water inside the reservoir when the user demands water). A more detailed explanation of PBLM models, data from residential loads (customer patterns), some scripts, and some characteristics of load demonstrators can be found on the authors’ web page [26].

The model was implemented in Matlab. Several tests with a residential HPWH were performed in the laboratory, and others were performed in homes to improve and validate the model as well as search for variations in the main parameters (thermostat setpoints, water inlet temperature, tank capacity, etc.) to better define the aggregation of the elemental models.

### 4.2. Characteristics of the Load and Laboratory Test Facilities

The HPWH analysed in this work is an Ariston Nuos Evo (80 L of capacity) installed in the laboratory. The main characteristics of the load are shown in Table 2. This appliance has two different heat sources: a heat pump and a resistor. There are three factory settings or modes of service (“eco”, “boost”, and “auto”). In eco mode, the load only uses the heat pump as a heat source (i.e., to run with a minimum consumption). In boost mode, both heat sources are used simultaneously to reach the target temperature in the minimum time (i.e., the appliance prioritizes service in the short term through maximum consumption).
Finally, in auto mode, the HPWH chooses between the heat pump and the resistor to reach the temperature selected in a maximum time of 8 h (i.e., a hybrid mode). This duality of supply and the three different modes presents some problems resulting in inefficient performance. However, a hybrid heat source also presents some opportunities, such as higher flexibility for DR after disabling the factory settings and changing the configuration and control of heat sources. For this objective, the load control was changed externally during our tests.

Table 2. Characteristics of Ariston Nuos-Evo HPWH.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity (L), Energy Label</td>
<td>80 L, A+</td>
</tr>
<tr>
<td>Rated Power of Heat Pump (W)</td>
<td>250 (avg)/350 (max)</td>
</tr>
<tr>
<td>Performance, COP (outdoor air at 7°C)</td>
<td>2.55</td>
</tr>
<tr>
<td>Max. Heating time (h)</td>
<td>5 h 35 m</td>
</tr>
<tr>
<td>Max. WH Temperature (°C)</td>
<td>55 1/62</td>
</tr>
<tr>
<td>Ancillary Resistor (W)</td>
<td>1200</td>
</tr>
</tbody>
</table>

1 Recommended temperature for an efficient operation of HP.

Broad, intrusive monitoring and control systems have been installed in the load and its environment to obtain and tune the parameters of the PBLM. The demonstrator system in the laboratory measures all weather, electrical, thermal, and end-use service variables with relevance to explain load demand and service.

To obtain all these variables, a multi-sensor (dwelling temperature and humidity), two temperature sensors (water inlet and outlet) and three thermocouples (inside the reservoir for obtaining hot, mixed, and cold zones temperature) were installed. In addition, two switches manage the switching of each heat source when DR policies are tested for validation. Two external thermostats were also installed to change the control switching of the HP and Resistor, disabling the factory settings of our appliance. Finally, a water flow controller enables the simulation of the discharging cycles of the HPWH with several water draw profiles provided by the control system.

Load monitoring and power management were implemented through IP-Symcon platform [27]. This system includes the management of several protocols together (KNX, EnOcean, M-BUS, Modbus, Siemens OZW/S5/S). The measurements of thermocouples are monitored through a data acquisition card linked to the same IP-Symcon platform. The system will be monitored and controlled in the future by an autonomous SymBox Pro unit [27], using different commercial protocols for communication and control that will be analyzed in detail (cost and benefits) for a further potential application to residential segments.

Figure 4 presents a scheme of the measurement and control systems installed in the laboratory. Figure 5a shows a picture of the appliance, its environment, and the monitoring system. Note the position of the own temperature (NTC) sensors (Figure 4) for resistors and compressors and the position of intrusive sensors (thermocouples “S”) installed to validate the model (Figure 5b).

Figure 6 presents a plot for some variables that have been monitored by IP-Symcon. As shown, temperatures at different zones in the tank (“S” labels in Figure 5b) are similar when the HPWH is near its steady state. In this case, the tank can be modelled as one mass/zone or “1C”, but temperature stratification appears when the customer demands hot water (in this case, two draws of 3 l/min for 10 min have been applied by our control system). It can be seen that temperatures at each of the three zones (mass) change with a different pattern. We emphasize that each one drives the two energy conversion devices (in this case, the temperature $X_2$ drives the start of the heat pump) because the internal sensors of heat sources are at different sites inside the tank (NTC sensors, Figure 5b). Moreover, HP demands change because the internal temperature of the water also changes (and the temperature gradient drives COP). For instance, the demand for energy conversion depends on $X_3$ due to the position of the HP condenser (Figure 5b). Figure 6 depicts the dependence between demand and temperature, and it confirms the sense of defining three
zones in the proposed model. In summary, $X_1$ defines load service (water draw/outlet; Figure 5b), $X_2$ defines the switching of the compressor, and $X_3$ defines the switching of resistors (if needed) and COP.

![Figure 4](image.png)

Figure 4. Scheme of measurement and control systems applied to HPWH laboratory demonstrator.

![Figure 5](image.png)

Figure 5. HPWH (Ariston Nuos Evo 80 L) monitoring system: (a) Holes through the tank for the intrusive layout of thermocouples; (b) Schematic of the HPWH unit.

![Figure 6](image.png)

Figure 6. An example of HPWH records that were performed during laboratory tests.
4.3. Electrical Modelling: Fast Response and Energy Conversion

From the point of view of using HPWH for fast services (i.e., AS), the response of heat sources is the main problem to be considered, specifically the latency of HP compressors that cause an additional and stochastic delay when applying ON signals (Figure 7a). This is irrelevant for a 5–15 min monitoring period in the traditional DR portfolio, but it becomes important when response can be achieved from some seconds to some minutes. To evaluate the effect and characterize delay into the HPWH model, a search was done. This is possible because the starting of the compressors and switch-on/off signals were monitored with a higher granularity (seconds). Thanks to the use of smart devices through IP-Symcon platform [27], the user can define sampling rates ranging from seconds to minutes to search for this delay. Figure 7b shows a histogram with some of the results obtained for the latency parameter.

![Figure 7. Latency in 80 L HPWH: (a) Evolution of power in a test example; (b) Histogram for OFF/ON latency trials.](image)

This mechanical latency—at the least, smart devices latency (if required in the evaluation of performance in very fast response events)—conditions the use of energy conversion sources of the model H\textsubscript{HP} and H\textsubscript{R}. The model can be programmed to include and account for this latency through a delay timer driven by a probability density function (according to Figure 7b), or it can be programmed to prioritize heat resistor response to avoid delay in fast response events (e.g., frequency regulation in AS markets).

Moreover, thermal generation (heat gain H\textsubscript{HP}; Figure 3) depends on COP and electrical demand. Prior studies have used a linear model like that reported by the Sustainable Technologies Evaluation Program in Canada [28] and fitted for our HPWH loads through laboratory tests and considering average COP data from the manufacturer for several units. Mathematically, this COP indoors is 10 °C (i.e., air temperature, tank temperatures X\textsubscript{2} and X\textsubscript{3} for the condenser zone):

\[
\text{COP} (X_2, X_d = 10 \, ^\circ \text{C}) = -0.011 \left(X_2 + X_3\right) + 3.30
\]

4.4. Model Parameters: Verification and Validation of the Proposed Model

It is necessary to perform several tests in the laboratory and some simulations in Matlab to obtain the parameters for the model. Load measurements have been collected for more than 4 months. Different cycles of water outlets with different heat sources (HP or resistor) have been programmed to observe the behaviour of the load and its response to different water consumption profiles (charge–discharge cycles). Moreover, different control strategies (DR) on supply have been tested (a single heat source or two sources) to verify the response of the model in transient and steady-state scenarios. Later, the model parameters were fitted by performing several simulations in Matlab, obtaining the accuracy and precision of the model with respect to the real database. An additional advantage of PBLM is that some initial values of parameters can be easily estimated based on the thermal processes that occur in the load and their environment. This makes the evaluation of final parameters more straightforward.
parameters easier. A trivial example for this initial estimation is the total capacity $C_t$ of the water tank can be obtained through physical-chemical characteristics of water and the geometry of the tank as

$$C_t = \rho V c_e = 0.99 \text{ kg/L} \times 80 \text{ L} \times 4.18 \text{ kJ/kgK} = 331 \text{ kJ/K} \quad (3)$$

where $\rho$ is the density of the water, $V$ is the total volume of the tank, and $c_e$ is the specific heat of water (4.18 kJ/kgK).

With these initial values, a genetic algorithm has been used to refine the value of parameters. The performance of the model has been verified using three common metrics: the Mean Percent Error (MPE), the Mean Absolute Percent Error (MAPE), and the Root Mean Square Error (RMSE). MPE has been selected to measure accuracy because it can describe the magnitude and direction of the bias. MAPE and MPE indicate the percentage of error between the temperature predicted and the real temperature inside the tank, while MPE can determine whether the temperature is over- or underestimated. The closer to zero both are, the more accurate the model is. To evaluate the precision, MAPE and RMSE have been selected. The lower the RMSE is, the more precise the model is.

The model designed and explained in Section 4.1 has been implemented in Matlab and tested with real data from the laboratory load demonstrator (Figure 5) with different duty cycles, a mix of internal heating sources, and water draw profiles. The parameters obtained for the model are depicted in Table 3.

Table 3. Parameters of the PBLM for the HPWH load.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hot-water zone capacity (L)</td>
<td>25</td>
<td>$C_3$ (kJ/K)</td>
<td>82.8</td>
</tr>
<tr>
<td>Mixed-water zone capacity (L)</td>
<td>35</td>
<td>$G_{L1}, G_{L2}$ (W/K)</td>
<td>1</td>
</tr>
<tr>
<td>Cold-water zone capacity (L)</td>
<td>20</td>
<td>$G_{C1}, G_{C3}$ (W/K)</td>
<td>0.125</td>
</tr>
<tr>
<td>$G_{E1}$ (W/K)</td>
<td>0.094</td>
<td>$\alpha$</td>
<td>0.3</td>
</tr>
<tr>
<td>$G_{E2}$ (W/K)</td>
<td>0.132</td>
<td>$\beta$</td>
<td>0.7</td>
</tr>
<tr>
<td>$G_{E3}$ (W/K)</td>
<td>0.075</td>
<td>$\theta_1$</td>
<td>0.12</td>
</tr>
<tr>
<td>$C_{tot}$ (kJ/K)</td>
<td>331.1</td>
<td>$\theta_2$</td>
<td>0.6</td>
</tr>
<tr>
<td>$C_1$ (kJ/K)</td>
<td>103.5</td>
<td>$\theta_3$</td>
<td>0.28</td>
</tr>
<tr>
<td>$C_2$ (kJ/K)</td>
<td>144.8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4 reports the results obtained through simulation for the evaluation and verification of the model, with the parameters presented in Table 3 for one week of tests as an example. As shown, Day 6 presents the maximum indices of temperature error in the mixed-water zone (WH2). In the case of the RMSE, the maximum error is $2.05 \degree C$. In the case of MPE and MAPE, the error is $-2.32\%$ and $2.65\%$, respectively. Negative values in MPE mean that the temperature is overestimated, while positive values show an underestimation of the temperature. In the hot water zone, maximum errors are shown on Day 7, with values of $1.556 \degree C$ for RMSE, $-2.02\%$ for MPE, and $2.35\%$ for MAPE. Finally, in the cold-water zone, RMSE and MAPE are the greatest for Day 2, with errors of $1.08 \degree C$ and $1.93\%$, respectively, while MPE is greatest on Day 1, with a value of $1.36\%$. In all water zones, the errors are less than $3\%$ and $3 \degree C$ (for RMSE), so it can be assumed that the proposed model performs properly.

As Day 6 is the day with the greatest errors, Figure 8 depicts measurements obtained from the load and the temperature values for the water zones obtained with the model (corresponding to Table 4) for this day. The water outlet flow, $q(t)$, and HPWH demand (both recorded for this test) are also included in Figure 8a.
Table 4. Metrics for the evaluation of the model performance (state variables $X_1$, $X_2$, $X_3$).

<table>
<thead>
<tr>
<th>Index</th>
<th>Zone</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Day 6</th>
<th>Day 7</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hot-WH1</td>
<td>0.997</td>
<td>1.133</td>
<td>0.904</td>
<td>0.874</td>
<td>1.093</td>
<td>1.200</td>
<td>1.556</td>
</tr>
<tr>
<td></td>
<td>Mixed-WH2</td>
<td>1.277</td>
<td>1.338</td>
<td>1.403</td>
<td>1.870</td>
<td>1.902</td>
<td>2.054</td>
<td>0.956</td>
</tr>
<tr>
<td></td>
<td>Cold-WH3</td>
<td>1.058</td>
<td>1.082</td>
<td>0.773</td>
<td>0.904</td>
<td>0.885</td>
<td>0.950</td>
<td>0.427</td>
</tr>
<tr>
<td></td>
<td>Hot-WH1</td>
<td>−1.135</td>
<td>−0.931</td>
<td>0.125</td>
<td>−0.367</td>
<td>−0.573</td>
<td>−1.252</td>
<td>−2.020</td>
</tr>
<tr>
<td></td>
<td>Mixed-WH2</td>
<td>−0.196</td>
<td>−0.994</td>
<td>−0.850</td>
<td>−2.062</td>
<td>−1.921</td>
<td>−2.319</td>
<td>−0.076</td>
</tr>
<tr>
<td></td>
<td>Cold-WH3</td>
<td>1.365</td>
<td>0.757</td>
<td>0.328</td>
<td>0.220</td>
<td>0.072</td>
<td>0.069</td>
<td>0.616</td>
</tr>
<tr>
<td></td>
<td>Hot-WH1</td>
<td>1.488</td>
<td>1.697</td>
<td>1.121</td>
<td>1.206</td>
<td>1.524</td>
<td>1.827</td>
<td>2.347</td>
</tr>
<tr>
<td></td>
<td>Mixed-WH2</td>
<td>1.864</td>
<td>1.468</td>
<td>1.611</td>
<td>2.273</td>
<td>2.260</td>
<td>2.652</td>
<td>1.088</td>
</tr>
<tr>
<td></td>
<td>Cold-WH3</td>
<td>1.448</td>
<td>1.932</td>
<td>1.476</td>
<td>1.698</td>
<td>1.776</td>
<td>1.945</td>
<td>0.719</td>
</tr>
</tbody>
</table>

Figure 8. Predicted and real profiles for the temperatures; water draw and power measurements for the tested HPWH (a) Prediction with the model. (b) Comparison of all WH zones.

5. Load Segmentation and Aggregation

5.1. Load Aggregation

Load aggregation is a basic requirement for the participation of small customers in the markets, but it can become a difficult task from technical, regulatory, and educational points of view. From a regulatory perspective, small customer segments usually face important barriers. For instance, Spain is one of the countries that have proposed significant barriers to small consumers [29] with respect to response requirements (e.g., a threshold above 1 MW for the capacity of response). This threshold involves a more complex aggregation through more and different appliances and, consequently, more heterogeneous loads, consumers (e.g., load service patterns, dwelling characteristics), and kinds of demand-side resources. From the point of view of EWH, this aggregation encompasses that load must be split into homogeneous (HCG) and quasi-homogeneous control groups (QHCG) according to the water tank size, customer patterns, or energy conversion technology. This segmentation of the overall end-use (water heating) makes the flexibility of demand easier and more effective. The participation of controllable HCG and QHCG loads in several markets and services seems necessary to achieve greater revenue and cost-effectiveness for customers and aggregators through sharing costs of more complex enabling technology (smart meters and controllers, sensors, gateways, etc.) necessary for more complex management (aggregation) of resources.

5.2. The Customer Demand Baseline

Aggregation is also important in evaluating DR&EE performance according to the objectives that are pursued. DR simulation or real measurements after DR (e.g., through a more effective NIALM [30], considering a higher granularity of data provided by the deployment of smart devices [4]), must be compared to its CBL, which is the theoretical demand of an aggregation of uncontrolled loads. The actual demand can involve penalties if DR resources are consuming less than the defined CBL during the availability periods [31].
PBLM can improve the evaluation of CBL, especially before and after DR is applied [30]. Some feedback from smart devices to the aggregator (demand, temperatures from some appliances) can also help in this task, such as the evaluation of offline flexible devices into the control groups.

For the simulation, a QHCG group of 80–110 L HPWH has been defined. It should be remembered that the average size of EWH tanks in Spain is around 90 L (Figure 1). Moreover, the WH manufacturer being considered (ARISTON [32]) sells and distributes residential HPWHs in this range of capacity. Aside from the tank capacity, standard patterns for the use of hot water have been considered, enabling a dispersion in the time of use of water demand. In the literature, other researchers have considered monitored DHW heat use, national and international standard profiles (e.g., [33] for Norway), and the estimated water draws according to specific WH demand profiles to suit specific tariffs [7]. In this paper, the authors have applied profiles based on EN 12831 European Standard to calculate heat loads in dwellings [34]. Figure 9 shows one of these profiles according to the size of the WHs being considered. Notice that the average HPWH load profile roughly represents a proportional reduction in the load shape of ERWH due to load shape diversity (see also Figure 2b).

![Figure 9. Elemental and aggregated demand service and profiles: (a) A typical WH water flow profile, q(t), used to determine the energy requirements of WHs according to EU standard [34]; (b) Aggregated WH demand (40 loads, 1200 W/load, simulation output each minute) with the previous water demand profile.](image)

This load profile explains a water temperature of at least 55 °C, which is the usual temperature of HPWH recommended by manufacturers to maintain efficiency (a maximum COP; see Table 2). Obviously, the demand profile presented in Figure 9 also depends on water inlet temperature (in this case, it is assumed to be 20 °C based on weather data). It depends on the week or season selected for the simulation. This can be done by changing PBLM inputs. Moreover, some efficiency measures can also be analyzed through PBLM (COP improvement, the insulation of the tank, change of patterns, etc.).

5.3. EWH Segmentation and Clustering

The characteristics of actual EWH classes in the residential segment are quite different: tank size, weather conditions, energy conversion technology, inhabitants and load service, and individual or common use. It seems necessary to perform some segmentation and classification in the WH population to assess strategies and to match controllable EWH best suited to each DR policy, finding the size of QHCGs. Moreover, developing methods to match customer loads to control policies and markets could increase the overall benefits and relevance of DR portfolio. The proposed classification in this paper is based on WH demand profile. This end-use demand can be achieved by aggregators through submetering or NIALM from representative customers (geographical area, income, kind of dwelling . . .).

ERWH and HPWH with different water draws and rated power (from 250 to 350W in the case of HPWH and from 700 to 2200 W in the case of ERWH) but with similar tank
sizes (from 75 to 100 L, around the average tank size in Spain) have been monitored and included for clustering. All the demand profiles were normalized to avoid the influence of the amplitude of demand in the segmentation. The clustering method was carried out by means of the R package “TSClust”, using the integrated periodogram distance \[35\] and the average linkage. Figure 10 shows the results of the clustering method applied to our example, where four different groups can be detected. Figure 11 depicts the demand profile inside each cluster. Note that the distance measure used focuses on the frequency domain instead of the time domain.

**Figure 10.** Classification of EWH profiles (each column represents WH daily load profile, pp, in the format dd/mm/yy). Each box defines a cluster (1 to 4).

**Figure 11.** Some representative WH demand profiles for each cluster: (a) cluster 1; (b) cluster 2; (c) cluster 3 and (d) cluster 4 (the color corresponds to clusters defined in Figure 10).
6. Results and Discussion

As stated in the introduction section, demand flexibility and change of patterns are required to face the increase of renewables in the generation mix. The contribution of end-uses to flexibility needs in the short term (and in longer time scales, for the next years) has been analyzed in different reports (e.g., [36]). Heating and Transportation leads this flexibility in daily and seasonal scenarios from 2022 to 2050. In the short term, more flexibility in heating is crucial, and the requirements for flexibility changes by 2050 are based on transportation segments. In this case, Electric Vehicles are a cornerstone for flexibility in the residential sector, but the conventional transportation segment (e.g., especially railways in several countries) also plays an important role (around 80% of flexibility requirements by 2050, [36]) through the development of Demand Response in those segments and its impacts in the overall power system through DR, Efficiency and Electrical Storage, as proposed in [37,38].

Electric Vehicles and the seasonal change in heating demand are out of the scope of this section, which is focused on heating and, specifically, water heating. In this way, and once the HPWH elemental model and different clusters have been identified (Section 5), the elemental models for loads with different parameters were simulated. Two different DR strategies were simulated to test the capabilities of HPWH loads to react and adapt their consumption to control targets. First, the demand for QHCG is controlled to maximize PV generation, which is a sound alternative for the operation of residential prosumers (the increase of self-consumption). Later, control intends to reduce peak demand, which is a conventional policy, for example, to reach revenues from Capacity Markets.

6.1. HPWH Aggregation Levels and Limits

As discussed in Section 5, load aggregation is a requisite for the participation of residential segments in markets through DR and so define QHCG groups. In our case, the aggregation of 100 HPWH loads, which are represented by the elemental model described in Section 4.1, is developed by the summation of the response of elemental models, each one driven by the different characteristics of the proposed QHCG (tank size range, dwelling temperature, water uses, etc.; see Table 5).

Table 5. Range of parameters for the aggregated HPWH load used to run PBLM probability density function (pdf).

<table>
<thead>
<tr>
<th>Parameter (Unit)</th>
<th>Reference Value</th>
<th>Range (and pdf) ¹</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water flow q(t) (L/min)</td>
<td>Figure 9a</td>
<td>±25% (normal)</td>
<td>Phase delay ±45 min (uniform)</td>
</tr>
<tr>
<td>Inhabitants</td>
<td>3</td>
<td>3–4 (uniform)</td>
<td>80 L capacity for three inhabitants</td>
</tr>
<tr>
<td>Tank capacity (L)</td>
<td>80 L</td>
<td>80–100 L</td>
<td>Changes in voltage supply</td>
</tr>
<tr>
<td>Ancillary resistor (W)</td>
<td>1200 W</td>
<td>±10% (normal)</td>
<td>Depending on the temperature gradient.</td>
</tr>
<tr>
<td>HP Power (W)</td>
<td>250 W</td>
<td>250–300 W</td>
<td>Manufacturer data (80 L and 100 L)</td>
</tr>
<tr>
<td>COP (air at 7 °C)</td>
<td>2.5</td>
<td>2.5–2.9</td>
<td>Changes in voltage supply</td>
</tr>
<tr>
<td>Inlet temperature (winter)</td>
<td>10 °C</td>
<td>±2 °C (uniform)</td>
<td>According to seasonal and weather data</td>
</tr>
<tr>
<td>External temp (winter)</td>
<td>18 °C</td>
<td>±2 °C (uniform)</td>
<td>Indoor temperature of dwelling</td>
</tr>
<tr>
<td>Thermostat setpoint</td>
<td>55 °C</td>
<td>55–62 °C</td>
<td>HP max efficiency at 55 °C</td>
</tr>
</tbody>
</table>

¹ Probability density function.

Usually, energy aggregators oversee this task, but due to the spread of loads and customer characteristics, some problems arise during the deployment of DR policies. For instance, aggregators can change ON/OFF periods (or Smart Thermostats settings) to adapt the total consumption to the DR targets, but these actions always impact the customers’ comfort. For this reason, the software also surveys that the temperature in the mixed-water zone of each tank is always in the range 50–62 °C (Figure 12). As a rule, at the aggregation stage, if a control approach causes more than 10% of households to experience severe hot water run outs, the approach is assumed to be unacceptable for the entire QHCG.
which becomes an additional barrier for these customer segments.

Profile; (tank to guarantee the customers' comfort during and after DR. PBLM software surveys the behavior of temperatures (state variables) inside the tank to guarantee the customers' comfort during and after DR.

For every month are depicted in Figure 13.

time, PBLM software surveys the behavior of temperatures (state variables) inside the tank to guarantee the customers' comfort during and after DR.

An alternative is the use of energy storage (batteries), but this alternative involves additional capital costs, which becomes an additional barrier for these customer segments.

6.2. Evaluating the Flexibility of HPWH: Prosumers

New PV generation in residential segments, driven by economic incentives, has increased the number of consumers becoming prosumers (consumers involved in energy generation activities through small renewables; in the proposed scenario basically PV generation and small consumer segments). However, sometimes, these prosumers cannot take full advantage of the energy they generate, as the consumption and generation periods do not match adequately. Moreover, net-demand evaluation (e.g., short-term load forecasting to define bids in energy markets) is less accurate because PV generation is more unpredictable than "conventional" demand, and this makes it more difficult to evaluate net demand (i.e., loads demand minus PV generation) requirements. Consequently, aggregators and balance responsible parties can foresee more problems in energy balance concerns due to the increasing load forecasting errors in power systems areas with a higher penetration of these prosumers. For this reason, the use of Demand Response strategies applied to thermostatically controlled loads, such as HPWH loads, can improve the performance of these systems, but HPWH should be flexible enough to increase and decrease demand to follow changes in renewable generation (or short-term generation forecasts). An alternative is the use of energy storage (batteries), but this alternative involves additional capital costs, which becomes an additional barrier for these customer segments.

The main objective of this simulation is to delay the consumption period of the HPWH to the hours in which more PV generation is available. In this paragraph, the flexibility of HPWH loads to follow the curve of PV generation has been tested. At the same time, PBLM software surveys the behavior of temperatures (state variables) inside the tank to guarantee the customers’ comfort during and after DR.

The PV system studied is a real 45 kWp PV plant installed in the south-east of Spain. The PV panels are fixed facing south and tilted 30°. The PV generation profiles (average) for every month are depicted in Figure 13.

6.2. Evaluating the Flexibility of HPWH: Prosumers

New PV generation in residential segments, driven by economic incentives, has increased the number of consumers becoming prosumers (consumers involved in energy generation activities through small renewables; in the proposed scenario basically PV generation and small consumer segments). However, sometimes, these prosumers cannot take full advantage of the energy they generate, as the consumption and generation periods do not match adequately. Moreover, net-demand evaluation (e.g., short-term load forecasting to define bids in energy markets) is less accurate because PV generation is more unpredictable than “conventional” demand, and this makes it more difficult to evaluate net demand (i.e., loads demand minus PV generation) requirements. Consequently, aggregators and balance responsible parties can foresee more problems in energy balance concerns due to the increasing load forecasting errors in power systems areas with a higher penetration of these prosumers. For this reason, the use of Demand Response strategies applied to thermostatically controlled loads, such as HPWH loads, can improve the performance of these systems, but HPWH should be flexible enough to increase and decrease demand to follow changes in renewable generation (or short-term generation forecasts). An alternative is the use of energy storage (batteries), but this alternative involves additional capital costs, which becomes an additional barrier for these customer segments.

The main objective of this simulation is to delay the consumption period of the HPWH to the hours in which more PV generation is available. In this paragraph, the flexibility of HPWH loads to follow the curve of PV generation has been tested. At the same time, PBLM software surveys the behavior of temperatures (state variables) inside the tank to guarantee the customers’ comfort during and after DR.

The PV system studied is a real 45 kWp PV plant installed in the south-east of Spain. The PV panels are fixed facing south and tilted 30°. The PV generation profiles (average) for every month are depicted in Figure 13.

The control strategy applied to the aggregated HPWH is to limit consumption in the morning and compensate for this reduction during the hours that PV generation is
performed. The temperature of the mixed water ($X_2$) inside each tank remains between $50 \, ^{\circ}C$ and $62 \, ^{\circ}C$. Figure 14 depicts the simulation results for a day in which there is a reduction of the PV generation at 13:00 (i.e., the generation pattern changes with respect to monthly average due to weather changes; see Figure 13). Figure 13 shows the baseline profile for the HPWH consumption in red. The green curve represents the target profile for DR to improve the energy use from the PV system. Finally, the final profile for the HPWH demand after applying the DR strategies and the comfort conditions are shown in blue. Figure 14b shows the average temperatures inside the tanks of the HPWH loads for the simulated day.

**Figure 14.** DR control of HPWH loads to meet PV target generation profile on an individual day: (a) Demand profiles; (b) Average temperatures inside the tanks.

Simulation results show a delay in WH demand from 7:00 to 12:00. Solar production is used to supply the HPWH requirements. However, at 15:00, some of the HPWHs have reached their maximum temperature to guarantee efficiency in energy conversion ($62 \, ^{\circ}C$; [32]). In this case, the modified HPWH demand profile cannot meet the target. This drawback can be overcome using the ancillary resistor (to reach higher temperatures; i.e., $65 \, ^{\circ}C$), but this policy involves some risk: the possibility of customer burns. The use of a water mixing valve avoids this health risk, but its use is not very common in Spain.

Figure 15 depicts simulations for the daily average PV generation for two different months and seasons (November and July) representing different PV generation performances. With respect to demand, in November, the peak is similar, but it is delayed to 12:00, while in July, the peak is delayed to 10:30. In July, the WH end-use peak grows (Figure 15b, blue curve) due to a higher consumption of water. Nevertheless, the HPWH demand increase is balanced by the increase of PV generation and the commitment of DR (Figure 15, grey curves). Notice that DR target basically follows PV generation (see Figure 13). In this way, the net-demand decreases in both cases (Figure 15, blue curve minus grey curve).

**Figure 15.** DR control of HPWH control group (QHCG) to meet PV monthly average generation profiles: (a) November; (b) July.
Some data about the goodness of DR strategies for prosumers are presented in Table 6. Although the HPWH demand is increased when DR is applied, the net demand with DR is reduced. This benefits prosumers because it avoids problems with the injection of power into the network. For instance, the development of control strategies to demand increases self-consumption around 15–30%. Notice that this depends on the PV energy generated and the capacity of WH loads to increase their temperature (e.g., through a mixing valve or the use of an ancillary resistor). As stated before, the first option is marginal in the Spanish residential sector because these mixing valves require additional capital and installation costs (e.g., €100–200 is the capital cost of a valve) and periodic inspections to ensure a properly functioning system, especially in several areas in Spain with a hard water supply (i.e., high concentrations of calcium and magnesium ions, which affects the WH and ancillary resistors performance). Nevertheless, mixing valves have several benefits: first, they enable WH to be operated at higher temperatures (preventing the growth of Legionella and increasing storage capacity); second, they can reduce the size and power requirements to provide capacity during larger time periods, and finally, they assure constant hot water temperature to the customer that avoid water losses due to low or high temperatures during the service. This option will be considered in more detail in the authors’ future research.

Table 6. Performance of HPWH following a PV dispatch.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Individual Day</th>
<th>November</th>
<th>July</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV generation</td>
<td>103 kWh</td>
<td>130 kWh</td>
<td>251 kWh</td>
</tr>
<tr>
<td>HPWH agg demand without DR</td>
<td>160 kWh</td>
<td>163 kWh</td>
<td>147 kWh</td>
</tr>
<tr>
<td>HPWH agg demand with DR</td>
<td>163 kWh</td>
<td>165 kWh</td>
<td>169 kWh</td>
</tr>
<tr>
<td>Net demand without DR</td>
<td>112 kWh</td>
<td>108 kWh</td>
<td>86 kWh</td>
</tr>
<tr>
<td>Net demand with DR</td>
<td>82 kWh</td>
<td>76 kWh</td>
<td>55 kWh</td>
</tr>
<tr>
<td>Use of own PV without DR</td>
<td>46.6%</td>
<td>39.9%</td>
<td>29.4%</td>
</tr>
<tr>
<td>Use of own PV with DR</td>
<td>79.1%</td>
<td>69.0%</td>
<td>45.3%</td>
</tr>
<tr>
<td>Increase in self-consumption</td>
<td>32.5%</td>
<td>29.1%</td>
<td>15.9%</td>
</tr>
</tbody>
</table>

Both options involve an additional cost to the user. For this reason, customers and aggregators should benefit from other DR revenues through their participation in complex products, services, and markets.

6.3. Evaluating the Flexibility of HPWH: Peak Savings

The ability of the loads to modify their consumption to reduce their maximum peak (from 10% to 50%) was also analysed. Specifically, this is accomplished by applying peak shaving policies to respond to a DR event. Again, the temperature of each HPWH load must be in the range between 50 °C and 62 °C, and the demand must not be reduced but delayed to maintain load service.

Figure 16 depicts some results for the peak shaving control. HPWH loads were committed to reducing their peak from 10% to 50%, but in every case, the real peak reduction reached is less than committed. The average temperature of the mixed water inside the tanks is always in the range from 51 °C to 59 °C, as shown in Figure 16b. Table 7 presents the results of the peak reduction dispatch. As said before, the maximum peak is always less reduced than expected, reaching a maximum percentage (−34.4% in −40% and −34.6% in −50% peak shaving dispatches). At this point, the loads do not have more capacity to reduce their peak or phase out their consumption without losing the service conditions (a minimum temperature of warm water). In this way, the limits of flexible demand can be defined and controlled more accurately through PBLM models.
The energy aggregator acts as an enrolling participant in DR and assists customers (and prosumers) in getting more profit from their flexible demand. Aggregators must achieve cost-effectiveness for DR. For this objective, they must develop customer participation in new and complex products to consolidate DR as a real option in the medium term and increase the small levels of participation and contribution to decrease peak demand (4–6%). To afford this new scenario, the development and refinement of new tools and methodologies that can explain and test the dynamic of loads and their environment are needed. EWHs, especially HPWH, have interesting characteristics for DR. First, the possibility to take more profit from their inherent capacity to store energy. They can act as “virtual batteries” and can balance renewables, whereas they contribute to energy efficiency and electrification (decarbonization). Finally, they have two conversion devices with different characteristics and dynamics of response (resistor and heat pumps), which can have advantages in different products and markets, especially in short-term response, which is basically unexplored for these segments.

This paper presents a simulation model (based on PBLM and aggregation methodologies, which are well-known in conventional DR) that can be adapted to be used in several DR policies and scenarios with different time horizons and scope, from a very fast response considering the delay of the compressor to a fast response considering stratification and hybrid switching of heat sources and a medium-term response through the change of storage patterns to follow renewables. The advantages of a grey-box approach such as PBLM are the universality of the model (suitable for several markets and policies), the use of well-known individual models (PBLM), and the easy and fast interpretation of results to react to DR control signals (flexibility of response) while maintaining comfort to ensure
the satisfaction and engagement of customers in DR. The proposed model shows good accuracy in the evaluation of water temperatures and demand (maximum MAPE errors around 2.35%).

The potential of the model to evaluate the flexibility of these efficient loads has been tested and demonstrated in two scenarios. First, results for the increased self-consumption of renewables show an increase in self-consumption of around 15–30%, depending on the month. This is relevant because other flexible loads can increase the flexibility and complexity of DR policies for both customers and aggregators. This will be a topic for future research. The second scenario is peak clipping. In this case, around 35% of peak reduction has been achieved. Because WH end-uses explain around 18–20% of residential demand, this flexibility could achieve around 6–7% of peak clipping in the segment; this is of interest to the power system.

Finally, this work also comments on the benefits of synergies associated with the use of other aggregator tools, such as NIALM, customer/load segmentation, and smart resources. These last resources have been a cornerstone to validate and tune the model both in steady state and control scenarios and to improve simulation results; consequently, they demonstrate and improve load flexibility in these small-demand segments. Additional interactions and synergies between models and technologies in other complex DR policies will be explored in future research.

**Author Contributions:** Conceptualization: A.G. (Antonio Gabaldón), A.G. (Antonio Guillamón), and M.C.R.-A.; methodology: A.G. (Antonio Gabaldón); software: A.G. (Antonio Gabaldón), A.G.-G. and A.G. (Antonio Guillamón); validation: A.G. (Antonio Gabaldón) and A.G.-G.; formal analysis: A.G. (Antonio Gabaldón); investigation: all authors; resources: M.C.R.-A. and A.G. (Antonio Guillamón); writing—original draft preparation: all authors; writing—review and editing: A.G. (Antonio Guillamón); visualization: A.G.-G. and A.G. (Antonio Guillamón); supervision, M.C.R.-A.; project administration: A.G. (Antonio Gabaldón) and M.C.R.-A.; funding acquisition: A.G. (Antonio Gabaldón), A.G. (Antonio Guillamón) and M.C.R.-A. All authors have read and agreed to the published version of the manuscript.

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**Conflicts of Interest:** Author Ana García-Garre was employed by the company MIWenergia. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

**Abbreviations**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>AS</td>
<td>Ancillary Services</td>
</tr>
<tr>
<td>CBL</td>
<td>Customer Baseline Load</td>
</tr>
<tr>
<td>COP</td>
<td>Coefficient of Performance</td>
</tr>
<tr>
<td>DER</td>
<td>Distributed Energy Resources</td>
</tr>
<tr>
<td>DR</td>
<td>Demand Response</td>
</tr>
<tr>
<td>DHW</td>
<td>Domestic Hot Water</td>
</tr>
</tbody>
</table>
EE Energy Efficiency
EIWH Electric Instantaneous Water Heater
ERWH Electric Resistance Water Heater
EWH Electric Water Heater
GHG Greenhouse Gases
GWH Gas Water Heater
GWP Global Warming Potential
HPWH Heat Pump Water Heater
HVAC Heat and Ventilation Air Conditioning
MAPE Mean Absolute Percent Error
MPE Mean Percent Error
NIALM Non-Intrusive Load Monitoring
PBLM Physical-Based Load Models
RES Renewable Energy Sources
RMSE Root Mean Square Error
SO System Operator
SThWH Solar Thermal Water Heater
SPDE Stochastic Partial Differential Equation
WH Water Heater

Symbols in elemental and aggregated PBLM models

\[ C_1, C_2, C_3 \] Thermal capacity of water tank zones (energy storage)
\[ c_e \] Specific heat of water
\[ q(t) \] Water flow
\[ D \] Differential operator
\[ G_{E1-2-3} \] Thermal losses from water to the environment through tank envelope
\[ G_{C1-2-3} \] Thermal losses coefficient (conduction) to the pipelines
\[ G_L \] Thermal losses coefficient (conduction) between water tank zones
\[ m_{HP}(t), m_R(t) \] Thermostat states of HP and resistors (discrete, 0/1, or continuous)
\[ H_{HP} \] Heat gains/extraction due to conversion to thermal energy (HP)
\[ H_R \] Heat gains/extraction due to conversion to thermal energy (resistor)
\[ X_{1-2-3} \] State variable. Indoor temperature in each tank zone.
\[ X_P \] Input. Temperature of input pipeline
\[ X_d \] Input. Temperature of the dwelling where WH is installed
\[ X_s \] Thermostat setting.
\[ WH_{1-2-3} \] Tank zones in the proposed model (to account for water stratification)

References


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