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Application of Scheduling Techniques for Load-Shifting in Smart Homes with Renewable-Energy-Sources Integration

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Abstract: The general context of this proposal is represented by the energy-efficient smart home that integrates renewable energy sources such as photovoltaic panels. The objective of this article is to minimize the amount of energy consumed from the national energy grid by producer-consumers of energy from renewable sources, in their own smart homes. In order to fulfill this goal, it was necessary to estimate the amount of renewable energy produced on the day-ahead horizon and to schedule the operation of controllable consumers in a smart home. To predict the amount of energy produced, two approaches were used: the first was based on data, and used techniques specific to artificial intelligence, more specifically, multilayer perceptron and radial-basis-function neural networks, and the second was based on models. The accuracy of the short-term prediction horizon of the techniques used was evaluated with quantitative performance indicators so that the most appropriate one in relation to the goal of the article could be selected to be used in the test scenarios. The scheduling of consumer functioning was based on their classification in relation to their ability to be controlled, and on the selection from the peer-reviewed literature of an optimization algorithm which, by load shifting from a smart home, ensured the optimal fulfillment of the objective function. The selected load-shifting algorithm was then integrated into and tested on a real database. The data used were monitored for two representative days, in terms of the amount of energy from renewable energy sources produced and consumed. The load-shifting algorithm proved its effectiveness through the results obtained and which are reported in the article.

Keywords: scheduling; forecasting; load-shifting; power generation; renewable energy sources

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1. Introduction

Recent trends in the energy market require prosumers (producers and consumers of energy from renewable energy sources) to take into consideration more complex energy-balance scenarios based on power and load balance, while the integration of large-scale renewable energy sources in the home increases and the number of home appliances introduces a not always predictable electricity consumption. Among the categories of well-known renewable sources, the ones that have experienced considerable development due to their successful integration into homes, are photovoltaic energy sources. The success is largely due to the fact that they can convert the Sun's energy into electricity without the help of heat engines and with fewer conversion failures.

Prosumers who chose to integrate this type of alternative source into their homes consider a number of factors that decisively influence the amount of green energy produced, among which we can mention: the solar constant at the location, the latitude of the location, the type of climate of the location, the local longitude of the location, the longitude of the standard meridian for the location, and the standard clock-time of the location. If the values of these variables are known, there are different mathematical models [1], called classical methods, with the help of which we can estimate the amount of energy produced from RES. In this framework, the problem can be regarded as time-series forecasting, for which different approaches can be considered [2–5].

The artificial intelligence techniques [6], include artificial neural networks (NN), such as multilayer-perceptron and feedforward neural-networks [7,8], radial-basis-functions neural networks [9], adaptive neuro-fuzzy inference systems [10], fuzzy-expert systems [11], multi-agent-based hybrid systems [12], convolutional neural networks [13,14], recurrent neural networks [15,16] and restricted Boltzmann machines [17]. Concerning long short-term memory architectures, these are effective in dealing with a variety of highly complex problems [18,19]. The incorporation of additional layers within deep-neural-network [20,21] architectures can significantly improve generalization performance, both for short- and long-term horizons. The main drawback of these highly complex intelligent topologies is the training computational-burden.

Unlike classical estimation methods, predictive models based on artificial-intelligence techniques are based on data. Therefore, a database is needed, resulting from smart-grid monitoring, which allows us to estimate the power generated from RES. The trend in the energy market is not only that of diversifying the sources of energy used in a smart home and estimating the amount of energy produced, but also that of using the energy available efficiently [22].

Household energy efficiency can be achieved mainly in two ways: by reducing total energy consumption or by consumption shifting. Consumption reduction refers to reducing the overall energy load, usually by increasing consumer awareness, shutting down appliances not in use, purchasing energy-efficient devices, or improving home construction and design. On the other hand, consumption shifting is focused on deferring certain loads over time, usually to off-peak periods, taking advantage of local production from renewable energy sources (RES) and off-peak tariffs in a liberalized energy market. Naturally, these two alternatives are not mutually exclusive, and can be employed together.

For determining optimal load-shifting, critical choices need to be made concerning the appliances to be managed, operational constraints of the grid, and the scheduling techniques to be considered. Scheduling is usually conducted over a future time-horizon, for which household demands and electricity generation can be predicted with accuracy. In this case, adequate and representative consumption and energy production from RES profiles are required. In addition, the core of the energy-management problem is intelligent load-shifting, which in an actual European scenario means minimizing energy payment by maximizing the energy from the self-consumption of renewable energy sources [23].

A wide variety of methods and techniques have been proposed in the scientific literature to improve the use of energy from RES through load schedules. These methodologies can generally be grouped into five categories: mathematical optimization, heuristic and metaheuristic methods, model-based predictive control, machine learning, and game-theory approaches [24].

The category of mathematical-optimization-based scheduling techniques includes non-linear programming problems, convex programming problems, and dynamic optimization problems. These techniques are the most popular choice for small and medium-sized scheduling problems addressed by home energy-management-systems. We have revised in our proposal the integration of mixed-integer linear-programming techniques (MILP) with different applications for energy scheduling purposes.

Thus, we have identified Sou, in [25], who proposes mixed-integer linear programming for minimizing the electricity cost in a smart home by assigning constraints such as enforcing uninterruptible and sequential operations for residential controllable loads. On the other hand, Tostado, in [26], uses the MILP for the optimal scheduling of a series of flexible appliances on various days of the week, involving different tariff options.

For example, [27] the authors describe the use of linear programming to schedule the electricity use of an industrial consumer for product manufacturing. For this type of consumer, additional restrictions are added to optimize the scheduling.

Srilakshmi proposes in [28] an approach for an electric vehicle charging/discharging-schedule rate in which the cars are modeled using MILP. The algorithm is used to maximize economic benefit for the prosumers, the owners of electric vehicles, with minimal battery degradation. In this approach, the optimization using MILP yields a definite optimal solution rather than a meta-heuristic optimization solution.

In his work, Koltsaklis [29] determines the optimal day-ahead energy scheduling of all load types for a smart home, through a cost-minimization objective function. The hybrid prediction model combines the k-medoids algorithm for performing the clustering of the training set and for input selection with the computing of the prediction using the Elman neural network.

In the general context of an energy-efficient smart home that integrates renewable energy sources such as photovoltaic panels, the objective of this article is to minimize the amount of energy consumed from the national energy grid by producer-consumers of energy from renewable sources, in their own smart homes. In order to fulfill this goal, it is necessary to estimate the amount of renewable energy produced on a day-ahead horizon and to schedule the operation of controllable consumers in a smart home. In consequence, the smart-prosumer framework, which supposes the smart-home-appliance consumption-classification and power-generation from renewable sources, is discussed in Section 2 of this article. Then, Section 3 introduces the mathematical formulation of the load-shifting algorithm and the principles of scheduling of energy consumption. Section 4 presents the numerical results obtained from a real prosumer database, and underlines the advantages of the proposed approach. Finally, in Section 5, conclusions and future research directions are presented.

2. Energy-Management Framework

2.1. Photovoltaic Power Generation

In the context of smart homes and new trends oriented towards sustainable development, the use of renewable energy sources (RES) proves to be very promising.

In our approach, firstly this problem of prediction was regarded as time-series forecasting, for which different approaches are considered in the literature [30].

We applied the model proposed by Han [31], to estimate the power generated by the photovoltaic (PV) panels, which is presented in Equations (1)–(5), and which is a function of the solar radiation incident on the modules and the ambient temperature. This method obtains the parameters through meteorological measurements and the panel manufacturer's manual.

Thus, the power generated from RES (denoted by P_{PV}) is computed as:

$$P_{PV} = N \cdot FF \cdot V \cdot I \tag{1}$$

$$FF = V_{mppt} - I_{mppt} \cdot V_{OC} - I_{SC} \tag{2}$$

$$V = V_{OC} - K_v(T_c - 25) \tag{3}$$

$$I = r[I_{SC} + K_i(T_c - 25)] \tag{4}$$

$$T_c = T_a + r(N_{ot} - 200.8) \tag{5}$$

where P_{PV} represents the amount of energy produced from RES and N represents the number of PV panels; FF is a dimensionless-form factor; V is the voltage in the PV module; I is the current in a PV cell; T_c represents the PV-panel temperature in degrees Celsius; T_a is the average environment temperature in the period; r is the solar radiation in kW/m^2; N_{ot} is the nominal operating-cell temperature; I_{sc} is the cell short-circuit current; K_i is a current/temperature coefficient; V_{oc} is the open-circuit voltage of the module; K_v is the thermal-stress coefficient in V/°C; V_{mppt} is the voltage at the point of maximum power; I_{mppt} represents the current at the point of maximum power.

Additionally, in order to accurately predict the amount of energy produced from renewable sources in the short term, we have designed and tested two neural-network architectures: multilayer perceptron (MLP) and radial-basis function (RBF). MLPs are usually used for performing short-time forecasting, being feedforward neural-network models, able to map sets of input data onto a set of appropriate output. They have multiple hidden layers of neurons, which are fully connected from one layer to the next. On the other hand, the RBF architectures used for performing short-time forecasting have an input layer, one hidden layer and an output layer. The neurons in the hidden layer contain Gaussian transfer-functions, whose outputs are inversely proportional to the distance from the center of the neuron. The characteristics of the proposed NN models are presented in Table 1.

Table 1. Characteristics of NN models.

Architecture	MLP-RN	RBF
Number inputs	1	1
Number layers	1 hidden layer with 5 nodes 1 output layer with 1 node	1 hidden layer with 5 radbas neurons 1 output layer with purelin neurons
Transfer functions	tansig—hidden layer purelin—output layer	gaussian—hidden layer purelin—output layer
Performance function	MSE	MSE and MAE
Training mode	Supervised	
Training method	Levenberg-Marquardt	
Train epochs	1000	
Initial MSE goal		0.0098
Initial spread		0.02719
Learning rate (lr)	0.05	
Tolerance (goal)	10^{-3}	

2.2. Home Appliances' Consumption

In our case, the considered smart home integrates not only a photovoltaic-power contribution and energy exchanges with the national power grid, but also smart loads. These smart loads are household appliances that can be analyzed and modeled, based on the characteristics and usage preferences of prosumers.

In the works [32,33], the smart-home appliances are divided into two categories (see Figure 1): non-schedulable (TCL), e.g., refrigerator, printer, microwave, television andhair-dryer, and schedulable home appliances (ECL), e.g., washing machine, air conditioner, iron, water heater, and electric vehicles. Non-schedulable appliances rely on manual control to complete a task, and are needed only when the users are home. Since the comfort level of users is quite sensitive to the timely services of non-schedulable appliances, their usage would usually not be delayed.

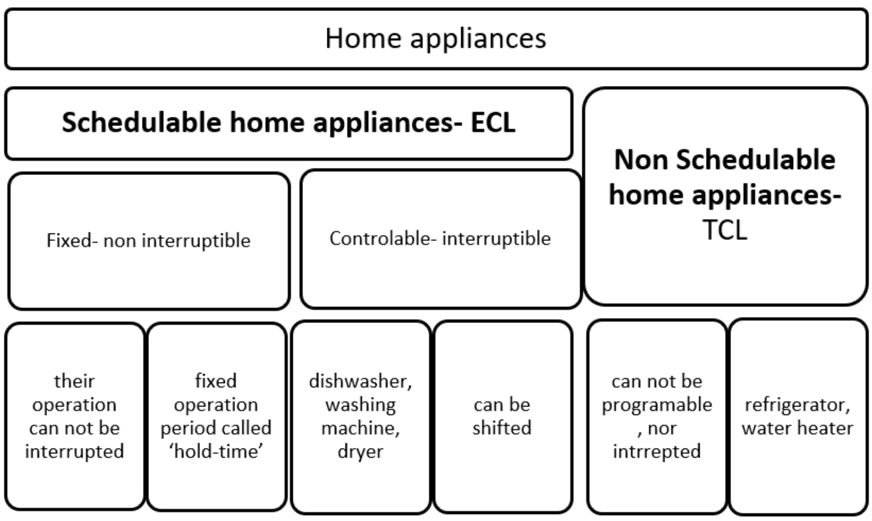


Figure 1. Classification of smart-home appliances.

The appliances which can complete a task without any manual control, such as air conditioners and water heaters, are schedulable [34]. These can be further classified into interruptible (controllable) and non-interruptible (fixed) in terms of the continuity of operation time [35]. Generally, interruptible appliances are usually more schedulable than non-interruptible ones. The non-interruptible appliances are constrained by a fixed operation-period called the hold-time [36], and this should be satisfied; namely, the washing-machine operation has to be completed for the task of the dryer to be able to start up.

Koltsaklis, in [24], presents the home appliances with their specific characteristics, including the load-type, and the power consumed (kW). Although it is possible to monitor the electrical consumptions of each appliance in the dwelling, only some appliance categories can be identified as "shiftable loads". These belong to the category of "periodically used appliances without human interaction" class in the energy-management problem.

The household-energy-management problem includes appliance constraints which are related to how household appliances are modeled, the appliance-model simplicity, and the lack of detailed consumption-profile data for controllable appliances.

The total energy consumed at each time slot, t, by all types of appliances from a smart home can be calculated by Equation (6):

$$P_{total}(t) = P_{fixed}(t) + P_{controllable}(t) + P_{TCLs}(t) \tag{6}$$

where P_{fixed} is the amount of energy consumed by fixed appliances, $P_{controlable}$ is the amount of energy consumed by controllable appliances and P_{TCLs} is the amount of energy consumed by non-schedulable appliances.

The demand and supply balance is a major concern for prosumers, and is directly affected by consumer behavior, the amount of energy available, and energy tariffs.

3. Load-Shifting Using Scheduling Techniques

3.1. Scheduling Framework

We will focus in this paper on the first category of deterministic optimization-based methodologies, because our problem formulation can be formalized as a linear optimization-based programming problem.

The class of problems considered in this paper is represented by the scheduling of home-appliance loads to minimize the cost paid by the prosumers for the energy consumed from the national energy grid. This category is a scheduling one, because it involves finding a least-cost schedule to process a set of orders, denoted by I, using a set of dissimilar controlled or uncontrolled home-appliances, denoted by M. The processing of an order, $i \in I$, can only begin after the release date, r_i, and must be completed at the latest by the due date, $\mathrm{d_i}$. Order i can be processed on any of the appliances. The processing cost and the processing time of order, $i \in I$, on appliance $m \in M$ are Cim and pim, respectively.

In these terms, the previously stated objectives could be formalized in this way: the main decisions involved in this scheduling problem are the assignment of orders to appliances, the sequence of orders to each appliance, and the start time for all the orders, to minimize the processing cost of all the orders.

3.2. Load-Shifting Algorithm

Since the objective function and constraints in this context are strictly expressed by linear relationships, being binary programming, we have considered mixed-integer linear programming (MILP) [26] as a suitable approach.

In this context, the energy-scheduling problem can be expressed (see Equation (7)) as the minimization of a cost function, given a certain number of electrical tasks, N_{tasks}, (e.g., the appliance starts) to arrange in $\mathrm{N_{TIME}}$ time samples:

$$\min_{w,\,L,\,C} \sum_{k=1}^{N_{task}} \sum_{i=1}^{N_{time}} w_k(i) L_k(i) C_k(i) \tag{7}$$

where $w_k(i)$ expresses whether or not a task is running on time, $C_k(i)$ is the energy cost at time i, and $L_k(i)$ is the energy consumed by the task in the time interval, i.

In particular, this minimization problem is subject to the following constrains (Equations (8)–(10)), considering the total power consumed at each time and the absence of interruptions for each task:

$$\forall\, \bar{i} \rightarrow \sum_k w_k(\bar{i}) \cdot L_k(\bar{i}) \leq P_{max} \tag{8}$$

$$\forall\, \bar{k} \rightarrow w_{\bar{k}}(i) = 1,\ \forall\, i:\ T^{start} < i < T^{end} \tag{9}$$

$$C_{\bar{k}}(\bar{i}) = \begin{cases} R(\bar{i})\ if \sum\limits_{k \neq \bar{k}} w_k(\bar{i}) \cdot L_k(\bar{i}) > P_{PV} \\ 0\ if \sum\limits_{k \neq \bar{k}} w_k(\bar{i}) \cdot L_k(\bar{i}) \leq P_{PV} \end{cases} \tag{10}$$

The shiftable tasks can set $w_k(i)$ to 1, according to a determined policy.

For each shiftable load, k, we consider Equation (11):

$$J(i) = \hat{P_{PV}}(i) - \hat{L_{TOT}}(i) \tag{11}$$

where $\hat{P_{PV}}(i)$ is the PV production forecasted at time i, and $\hat{L_{TOT}}(i)$ is the average consumption pattern for the considered day of the week. $\hat{L_{TOT}}(i)$ is computed by averaging the last 10 days and excluding the power consumed by the shiftable loads.

We then have to find the best timing to start the task minimizing the costs, as Equation (12) shows:

$$\min_i [\![J(j) - L_k(j)]\!] C_k(j) unde\ j = i, \ldots, i + T^{op} \tag{12}$$

where $L_k(j)$ is the power consumed by the load at the relative time j, $C_k(j)$ is the energy cost and T^{op} is the total cycle-time of the load.

4. Determining Optimal Load-Shifting Using Scheduling Techniques

4.1. Test Conditions and Strategy

In this section, the results obtained after the implementation of the load-shifting algorithm in the LabView software are presented.

The energy-consuming appliances considered in the scenarios reported here, selected from those presented in the section dedicated to the home appliances' consumption, are presented in figures below. The washing machine (Figure 2) and the dishwasher (Figure 3) are considered as being, in our scenarios, priority controllable-consumers, meaning loads whose consumption interval can be established according to the energy produced from RES, but once they are turned on, it is preferable not to turn them off. In addition, they have the ability to be shifted, fully or on a specific operation-cycle (see Table 2 for washing machine), to run at later intervals.

On the other hand, the vacuum cleaner (Figure 4) is an interruptible controllable-consumer, because its consumption interval can be set according to the energy produced, and its operation can be interrupted.

Table 2. Washing-machine power consumption during the operating cycles.

Operating Phase	Min. Power [W]	Max. Power [W]	Operation Time [min]
Movement	27.2	2100	26
Pre-heating	5	300	6.6
Heating	206.5	2200	59.7
Maintenance	11.0	200	19.9
Cooling	10.8	500	10
1st rinse	10.3	700	10.4
2nd rinse	9.9	700	10.3
3rd rinse	23.6	1170	19.8

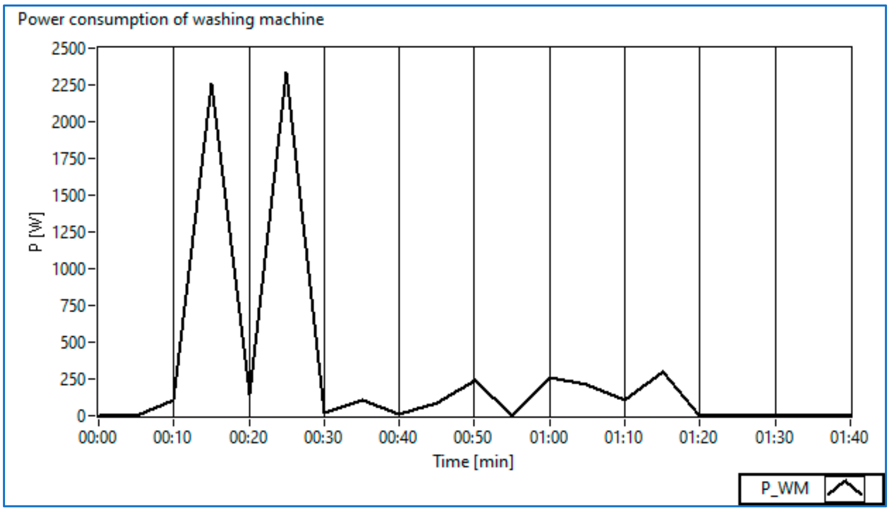


Figure 2. Power consumption (P_WM) during an operation cycle for washing machine.

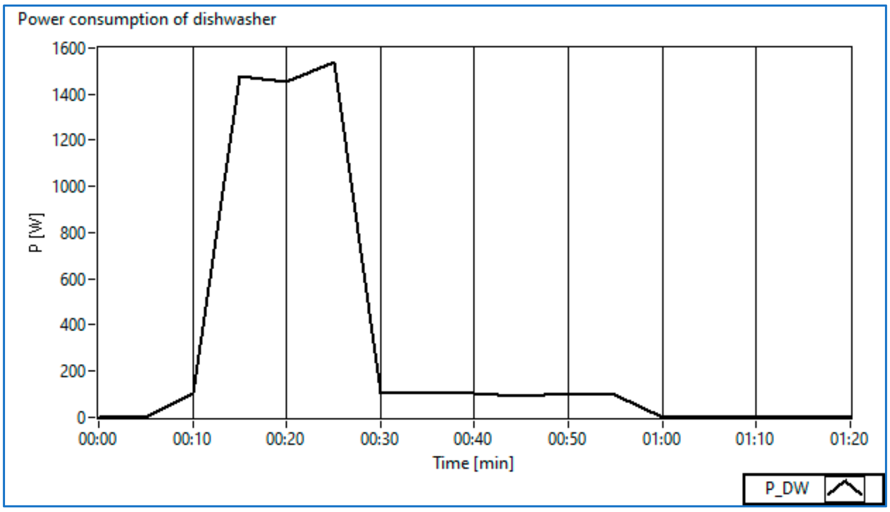


Figure 3. Power consumption (P_DW) during an operation cycle for dishwasher.

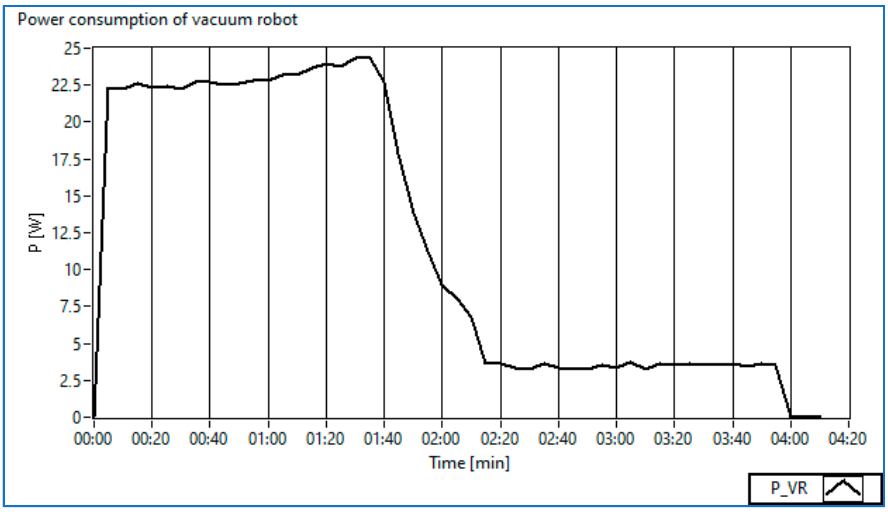
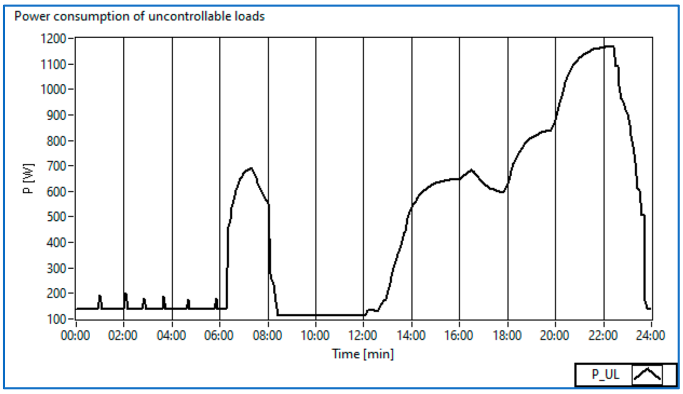
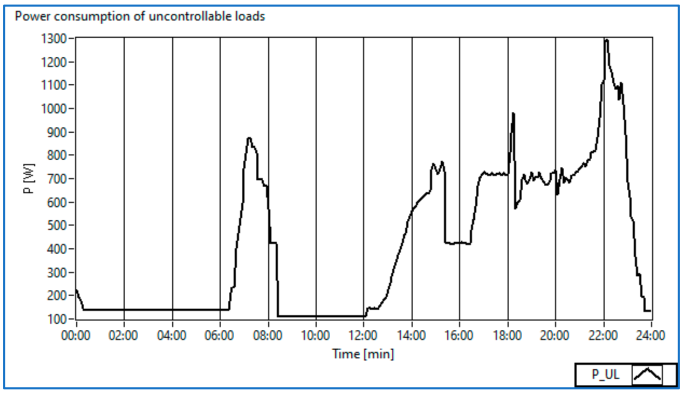


Figure 4. Power consumption (P_VR) during an operation cycle for robot vacuum.

In addition to these controllable consumers, in our case, some uncontrollable consumers chosen for the study, such as room lighting, a hair-dryer and a microwave oven, whose consumption is shown in Figure 5. Two scenarios were considered: scenario 1 for the 31 May 2022 (Figure 5a) and scenario 2 for the 11 November 2022 (Figure 5b).



(a)



(b)

Figure 5. Power consumption (P_UL) for uncontrollable loads: (**a**) scenario 1; (**b**) scenario 2.

The considered house has an installed power capacity from photovoltaic-energy sources, of 3.3 kW. The characteristics of the 12 PV panels integrated ino the smart grid, produced by Luxor (ECO LINE P60-275W) are presented in Table 3 The system contains the Huawei SUN2000-3KTL inverter.

Table 3. Characteristics of PV panels.

Model of PV Panel	No.	Characteristics (Per Module)							
		P_{nom}	C	I_{nom}	V_{nom}	I_{SC}	V_{OC}	T_{ref}	N_S
PV, Luxor, 275 W, Polycrystalline	12	275 W	60	8.77 A	31.42 V	9.27 A	38.58 V	25 °C	12

P_{nom} = nominal output power; C = the number of cells; I_{nom} = nominal current; V_{nom} = nominal voltage; I_{sc} = short-circuit current; V_{oc} = open-circuit voltage; T_{ref} = reference temperature; N_S = the number of solar panels connected in series.

4.2. Case Studies and Results

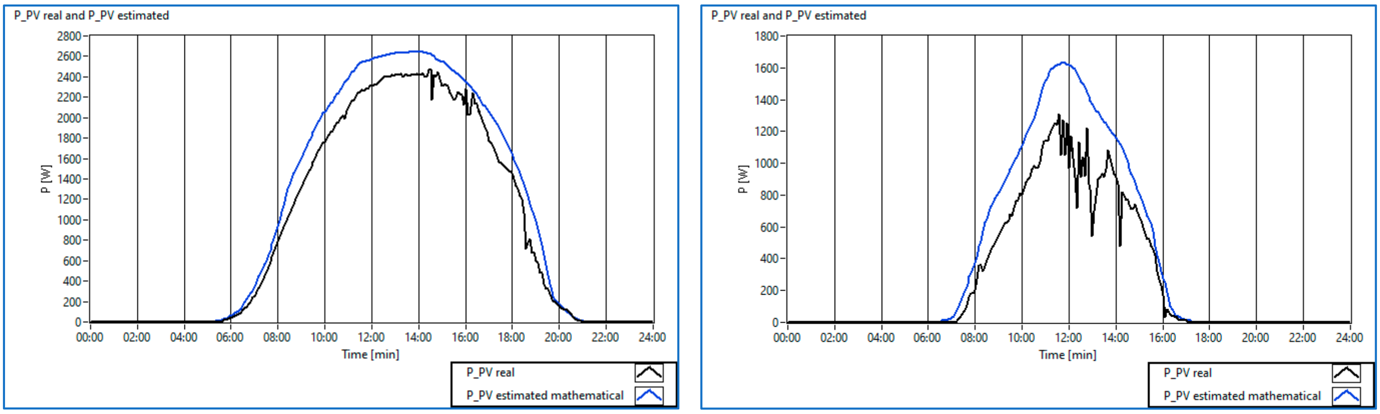
The system was able to meet the energy-load demand from May through August, even with the excess energy which can be stored in the battery system. For this reason, we considered a day in June for scenario 1. From October through April, the PV system was deficient in meeting the energy-load demand. To put in evidence this fact, for scenario 1 we considered a day in June as a reference. More precisely, to build the test scenarios, two representative days for the load and energy produced by RES were considered: the 2 June 2022, and the 12 November 2022.

The data used in the predictions were monitored for solar radiation and ambient temperature. The simulations were run over a 1-day time-horizon, with a time-step of 5 min.

Firstly, considering the mathematical model in Equations (1)–(5), we obtained an estimated profile of the PV power generated by the PV panels in relation to the real PV power monitored. These results are depicted in Figure 6a,b, for both scenarios.

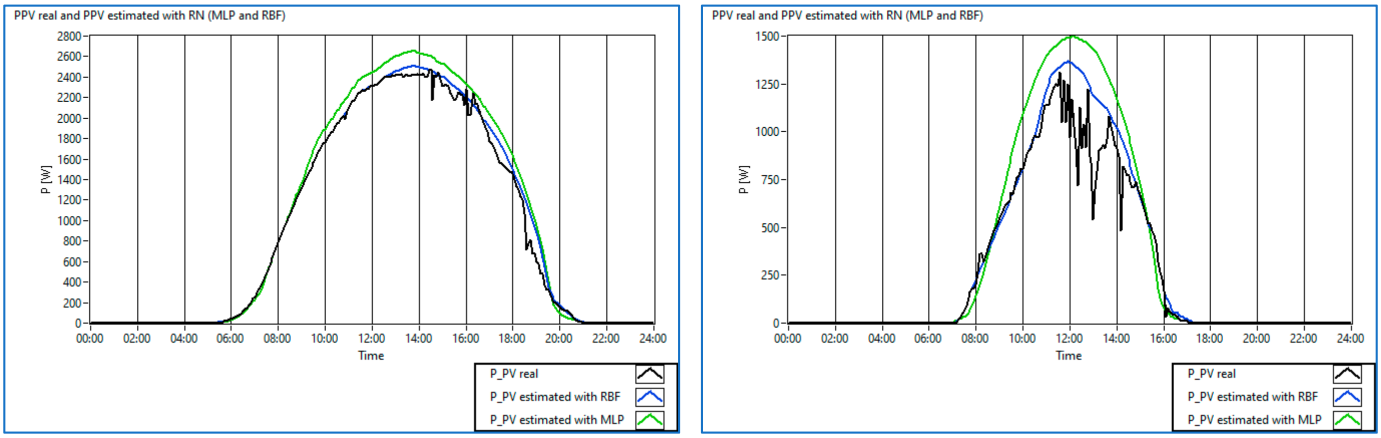
Secondly, similar profiles were predicted with the RN-MLP and RN-RBF architectures proposed in Section 2.1. Figure 7 shows the power-curve forecasted by RN-MLP (green), RN-RBF (blue) and real PV-power (black), for both scenarios.

The performance of the forecasting approaches for different prediction horizons was measured using root-mean-square error (RMSE) and mean absolute percentage error (MAPE) between the predicted values and the real measurements monitored on a grid of PV panels with 3.3 kW installed power. The model with the smallest RMSE and MAPE, for a day-ahead prediction horizon, was the RBF neural network. This profile of the energy generated from RES by RBF-RN was later used in the test scenarios. Table 4 shows the RMSE and MAPE values computed for the RN models and for the regression model (denoted "model").



(**a**) (**b**)

Figure 6. P_{PV} real and P_{PV} estimated with mathematical model for: (**a**) scenario 1; (**b**) scenario 2.



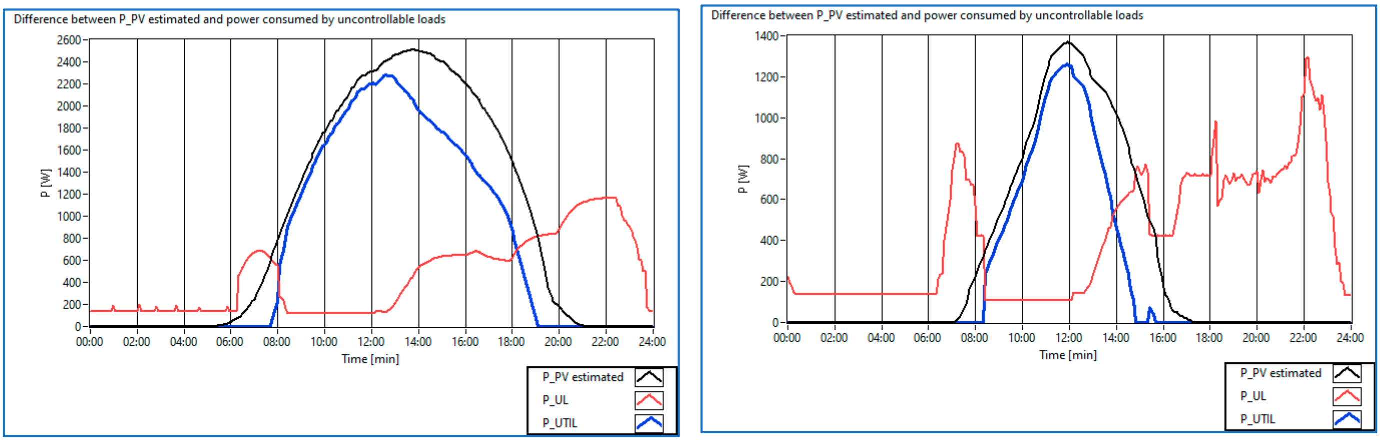
(**a**) (**b**)

Figure 7. P_{PV} real and P_{PV} estimated using MLP and RBF NN for: (**a**) scenario 1; (**b**) scenario 2.

Table 4. RMSE and MAPE.

Prediction Horizon	RMSE			MAPE		
	MLP-RN	RBF-RN	Model	MLP-RN	RBF-RN	Model
T+1	0.4186	0.5325	0.5725	0.0718	0.0579	0.0598
T+10	1.1395	1.228	1.228	0.2665	0.2863	0.4808
T+20	10.515	3.2758	3.2758	1.0757	0.915	0.915

The load-shifting MILP algorithm is satisfied by the scheduling approach, firstly by the constraint relating to the uncontrollable-load supply with energy from RES. Thus, Figure 8 presents the P_{PV} estimated by RBF (black), $\mathrm{P_{UL}}$ (the power consumed by the uncontrollable loads) (the red line), and $\mathrm{P_{UTIL}} = P_{PV} - \mathrm{P_{UL}}$ (the difference between the estimated P_{PV} and the power consumed by the uncontrollable-loads) (the blue line), for both scenarios.



(**a**) (**b**)

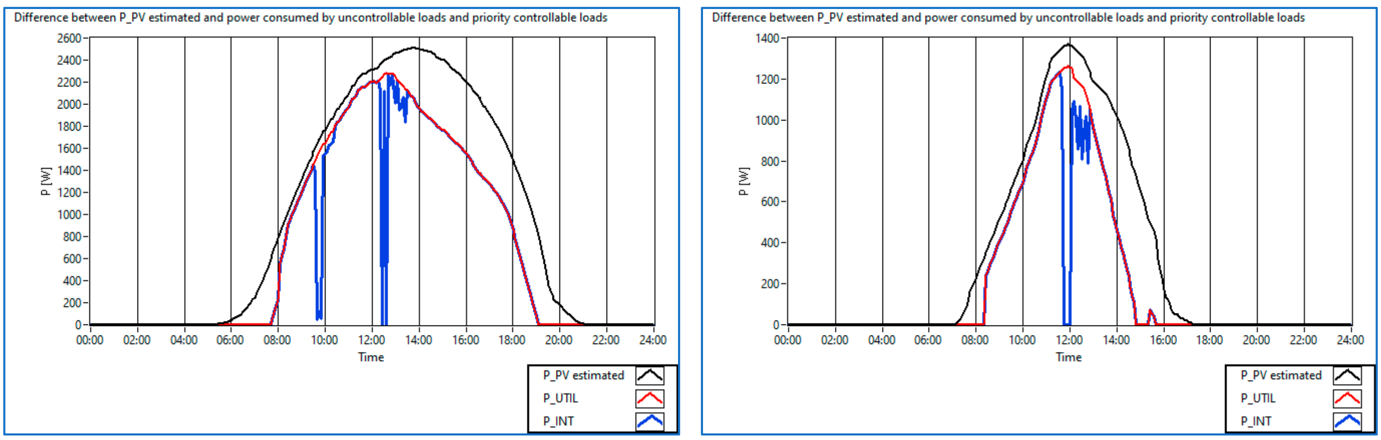
Figure 8. P_{PV} estimated by RBF, P_{UL}, DP_{PV1} for: (**a**) scenario 1; (**b**) scenario 2.

The second step of the shifting algorithm simulation consists in supplying the washing machine and dishwasher, which are controllable loads of first and second priority, respectively.

Figure 9 depicts the scheduling of the amount of energy for both scenarios. P_{PV} (the power estimated by RBF) is represented in black, P_{UTIL} (the difference between the estimated P_{PV} and the power consumed by uncontrollable loads) is the red line, and P_{INT} (the difference between the estimated P_{PV} and the power consumed by the uncontrollable-loads and the priority controllable-loads) is the blue line.

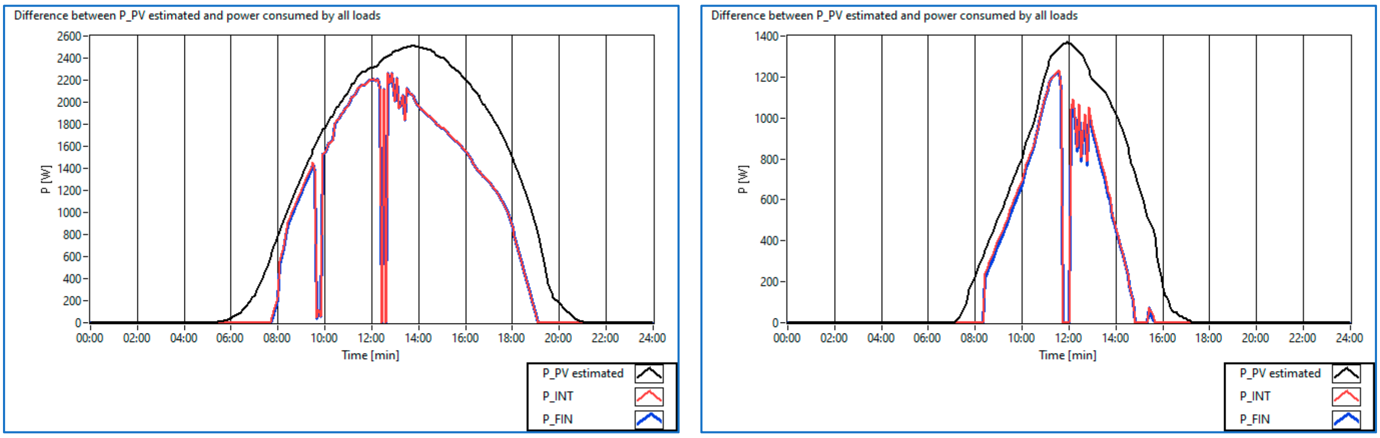
In our case: $P_{INT} = P_{PV} - P_{UL} - P_{WM} - P_{DW}$, where P_{PV} (power estimated with RBF), P_{INT} (between estimated P_{PV} and power consumed by uncontrollable-loads and priority controllable-loads), $P_{FIN} = P_{INT} - P_{P2}$ (P_{P2} = sum of all priority controllable-consumers which can be interrupted), P_{FIN} = difference between estimated P_{PV} and power consumed by all loads. In our case: $P_{FIN} = P_{PV} - P_{UL} - P_{WM} - P_{DW} - P_{VR}$.

The third step of the shifting-algorithm simulation consists in supplying the vacuum-cleaner load, as an interruptible controllable-consumer in which the operation can be interrupted. Figure 10 depicts the amount of energy after the third step of the algorithm for scenario 1 and scenario 2.



(**a**) (**b**)

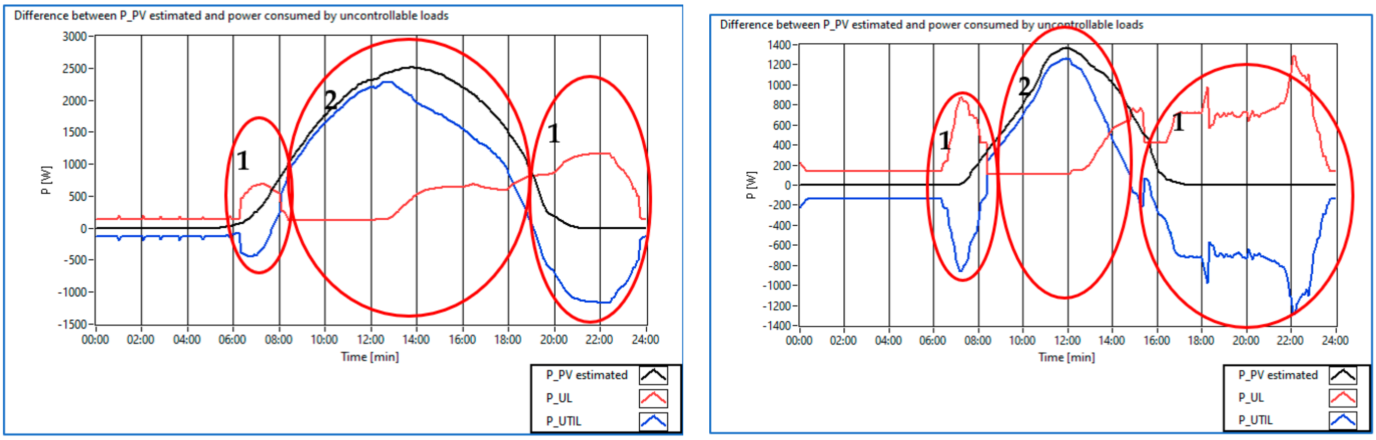
Figure 9. P_{PV} estimated by RBF, P_{UTIL}, P_{INT} for (**a**) scenario 1; (**b**) scenario 2.



(**a**) (**b**)

Figure 10. P_{PV} estimated by RBF, P_{INT}, and P_{FIN} for (**a**) scenario 1; (**b**) scenario 2.

In conclusion, the results obtained for the first scenario show that in the first third (the night and the morning period) of the day, more energy is consumed by uncontrollable-loads than produced. In the second third (the afternoon period), more is produced, and in the last third (the evening and the night period), much more is consumed than produced. Figure 11a shows that when we have a surplus of energy consumed compared with the energy generated by the photovoltaic system, then energy will be taken from the national grid (situation 1). When we have a surplus of energy generated by the photovoltaic system, it is preferable to turn on the controllable-loads (situation 2), in both scenarios.



(**a**) (**b**)

Figure 11. Scheduling for load-shifting optimization for: (**a**) scenario 1; (**b**) scenario 2.

On the other hand, in the case of the second scenario (Figure 11b), due to the weather conditions in November and the significantly reduced amount of energy from renewable sources compared to the case of the first scenario, the periods in which loads must be shifted with the help of the proposed algorithm are more and more difficult to achieve with optimization.

5. Conclusions and Work in Progress

This paper's goal is represented by the minimization of the amount of energy consumed from the national energy grid by producer-consumers of energy, from renewable sources, in their own smart homes.

Firstly, the general context of smart grids integrating renewable energy sources was defined. Beyond the identification of challenges and opportunities in the field during a bibliographic study, three methods were proposed to estimate the energy produced from renewable sources: two of them were based on MLP and RBF neural networks, and one used linear-regression methods for estimation. The performance of the forecasting approaches was measured using RMSE and MAPE, to find the differences between the predicted values and the real measurements monitored on a grid of PV panels with 3.3 kW installed power. The model with the smallest RMSE and MAPE was the RBF neural network. This profile of the energy generated from RES by RBF-RN was later used in the test scenarios.

The second issue addressed in the article was related to loads from smart homes. They were classified from the point of view of their ability to be controlled, their priority of operation, and the possibility of being interrupted or not while in operation. This preliminary analysis was necessary in view of the objective pursued in the article, of minimizing the amount of energy consumed from the national energy grid by load-shifting using scheduling techniques.

In the third section of the article, the algorithms for load-scheduling in a smart home were reviewed, and the MILP algorithm was selected to be integrated into the particular context of a smart home with an installed power-capacity of 3.3 kW.

In the fourth section of the article, the forecasting methods and the load-shifting algorithm were integrated and tested on a real database. The data were monitored for two days which were representative in terms of the amount of energy from RES produced and consumed, in June and November.

The load-shifting algorithm proved its effectiveness, through the results obtained and which are presented in Section 4.2, mainly in the periods when the amount of energy produced was reduced, due to meteorological conditions.

The limitations of the work reported here are due to the fact that the case study was carried out on a single family-smart-home, whose installed power from renewable energy sources was 3.3 kW, and to the fact that the number of controllable loads selected was limited by this framework.

In addition, the context was established by the national energy strategy, which encourages the installation of photovoltaic panels with an installed capacity of 3.3 kW in family homes, by granting a subsidy for this purpose. Therefore, the major interest is to identify energy-management systems for smart homes that ensure as much as possible a share of the consumption from the homes' own production.

The proposed framework can be extended with an analysis carried out on a smart home in which there would be, in addition to the production and consumption devices considered in our case study, a storage source of energy produced from renewable sources, such as battery banks. We consider that the influence would be significant, because it would make the prosumers' participation in the liberalized energy-market more flexible, as it would depend on the energy market price and the amount of available stored energy.

In addition, the work could be improved with a multi-objective optimization approach, by considering an additional criterion, for example, the way in which the degree of consumer comfort is impacted by load-shifting.

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