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Novel Functionalities of Smart Home Devices for the Elastic Energy Management Algorithm

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Abstract: Energy management in power systems is influenced by such factors as economic and ecological aspects. Increasing the use of electricity produced at a given time from renewable energy sources (RES) by employing the elastic energy management algorithm will allow for an increase in "green energy" in the energy sector. At the same time, it can reduce the production of electricity from fossil fuels, which is a positive economic aspect. In addition, it will reduce the volume of energy from RES that have to be stored using expensive energy storage or sent to other parts of the grid. The model parameters proposed in the elastic energy management algorithm are discussed. In particular, attention is paid to the time shift, which allows for the acceleration or the delay in the start-up of smart appliances. The actions taken by the algorithm are aimed at maintaining a compromise between the user's comfort and the requirements of distribution network operators. Establishing the value of the time shift parameter is based on GMDH neural networks and the regression method. In the simulation studies, the extension of selected activities related to the tasks performed in households and its impact on the user's comfort as well as the response to the increased generation of energy from renewable energy sources have been verified by the simulation research presented in this article. The widespread use of the new functionalities of smart appliance devices together with the elastic energy management algorithm is planned for the future. Such a combination of hardware and software will enable more effective energy management in smart grids, which will be part of national power systems.

Keywords: renewable energy sources; energy demand control; smart appliances; elastic energy management algorithm; GRASP algorithm; GMDH neural networks; regression method

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1. Introduction

The first-ever universal and legally binding global agreement on climate change was ratified at the Paris Climate Conference (COP21) in December 2015, and it is called the Paris Agreement [1]. The Paris Agreement laid out a global framework in order to prevent dangerous climate change by limiting global warming to a maximum temperature increase of 1.5 °C. The Agreement also aimed to strengthen the capacity of countries to cope with the effects of climate change and to support them in their own efforts to prevent global warming. The most developed plans and strategies in the area of counteracting global warming concern the countries in the European Union (EU). The European Commission has committed to achieving carbon neutrality in the EU by 2050. Details of these commitments have been formulated in the document "European Green Deal" [2]. One of the solutions offered by the European Green Deal is the "fit for 55" package, which provides for the revision of the Renewable Energy Directive (RED II) [3]. The EU expects this shift to help in achieving its new greenhouse gas emissions target of 55%. The revised RED II directive indicates a renewable energy share of at least 40% of the final energy consumption by 2030. This is a very ambitious target, and its fulfillment will require the connection of a significant number of renewable energy sources (RES) to the distribution network and a reduction in the number of conventional fossil fuel power plants.

Energy from RES is ecologically clean energy; however, its major disadvantage is the instability of its generation, which depends on weather conditions. Hence, there may be very high energy production from renewable sources in favorable weather conditions, e.g., from photovoltaic systems (PV) on a sunny day. It is obvious that such production can exceed the energy demand of the consumers. On the other hand, during unfavorable weather conditions, the system will have a shortage of energy because RES will not be able to generate it. Additionally, energy from PV systems will be available only during daylight hours; it will be at a very low level in the mornings and afternoons and will not be available at night. Complementarity between PV power generation and wind turbines may also not meet the energy demand. In order to take full advantage of the energy from RES, the following approaches should be applied: (i) use very expensive energy storage systems (ESS) [4,5], (ii) increase energy consumption during high generation and reduce in the period of non-generation of RES energy [6]. The overproduced energy from PV and other RES systems should be stored [5], used, or sent to places where there is a demand [6].

The energy generated by PV is unstable over time, and within a single week, there may be days with very small or very large but extremely variable energy production throughout the day, continuous production throughout the day, or only instantaneous power generation moments. Such variability in production requires actions that will allow it to stabilize. Therefore, in the local balancing of the power system, it is necessary to use or store as much energy as possible. Balancing energy generation with energy demand is of great importance both in systems with low voltage prosumer installations and in the case of large photovoltaic power plants. One of the conceptual approaches to harnessing energy overproduction is, as previously mentioned, to increase energy consumption during the period when a lot is produced. This approach requires appropriate energy demand management systems with the use of different loads. In a home environment, these may be home smart devices. The consumption of households should be increased during the large production of energy from RES, and their energy consumption should be reduced when there is a shortage of energy in the system or a lack of generation from RES [7].

The scientific literature describes a large number of concepts for managing electricity demand with home smart appliances (SA). Smart appliances are defined in this article as devices that respond to signals from the environment and working conditions in order to reduce the energy consumption of the tasks performed in relation to both electricity generation and demand. The concept of SA suggests that they perform not only their main functionality in a user-defined manner, but they also autonomously react to the environmental conditions in which they operate, e.g., for the supply of cheap, clean energy.

This article will present the use and integration of new functionalities into the energy demand management of smart home devices. These new functionalities will enable their operation to react to an external signal that carries information about energy production from local RES systems. In addition, for some smart devices, the functionality of the phased implementation of their standard functional programs will be defined. For example, a program in a dishwasher may be carried out in several stages, depending on the production of electricity. In the first stage, the process of heating the water and proper washing will be executed; in the second phase, pumping out the water and rinsing the dishes as well as the polishing process; and in the third phase, heating the water again and drying the dishes with hot steam.

To achieve good results from such a smart appliance, this device should receive information about the generation prediction from RES. Therefore, this article will present one of the concepts for predicting renewable energy generation using a neural network. The modeling of RES using statistical methods and artificial intelligence tools was presented in [8,9]. The operation of the proposed smart appliances with new functionalities will be tested using the

Elastic Energy Management (EEM) algorithm proposed in previous publications [7,10,11]. Then, on the basis of prediction, it will be possible to optimally manage the SA so as to optimally use the power generated by RES at a given time.

2. Elastic Energy Management

The main purpose of using EEM is to respond to an increase or decrease in energy availability in smart grid (SG) networks. If such a situation occurs, the central management unit sends a signal to distributed control devices (DCD) located at a given building or location. In order to better adapt to the requirements of end users or the Distribution System Operator (DSO) and the situations that may occur in SG networks, three variants of the EEM algorithm have been defined [7,10,11]: EEM_1, EEM_2, and EEM_3. The EEM_1 variant is applied to ensure user comfort when using SA devices. Electricity costs are also taken into account. EEM_2 is used during emergencies resulting from natural phenomena that damage the national power system (NPS) infrastructure. EEM_2 can also be used as a response to the peak demand phenomenon [12]. In the case of EEM_3, the overvoltage situation in the DCD is taken into account. This state occurs, for example, when connecting or disconnecting a large number of energy consumers. Figure 1 shows the structure of the power grid in which the EEM algorithm is used.

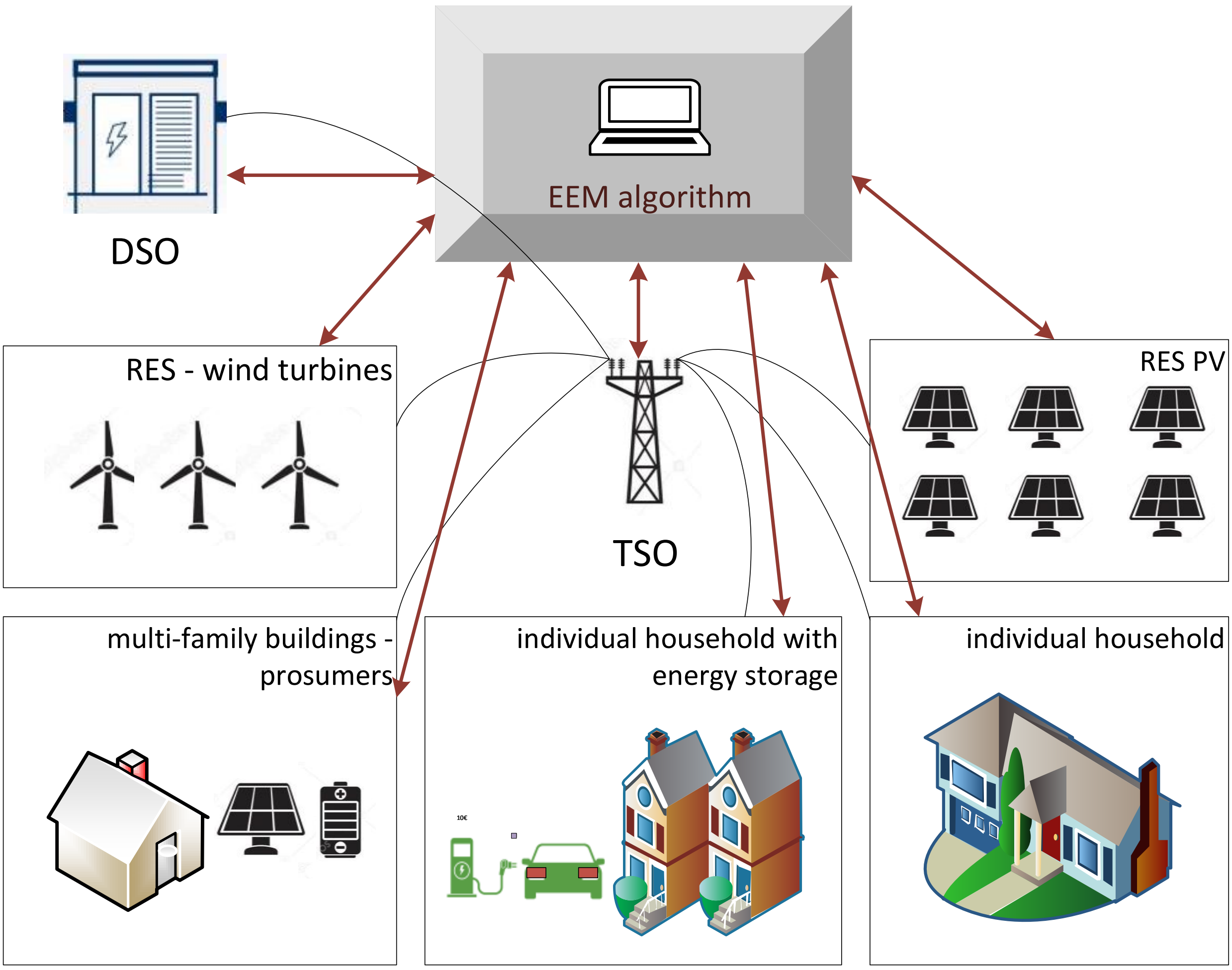


Figure 1. Structure of the power system with the EEM algorithm.

The implementation of individual EEM variants is based on the developed fitness function (F_{EEM}) [7,10,11]. F_{EEM} applies to the selection of new power settings for individual SAs during the operation of the Greedy Randomized Adaptive Search Procedure (GRASP) [13].

According to the EEM assumptions, each SA device requires that its properties be described with parameters. The set of defined parameters thus made it possible to define the model:

$$(P_{NOM}, P, pr, ts) \tag{1}$$

Earlier works [7,10,11] commonly considered parameters that were related to the basic properties of SAs. These included the definition of the nominal value of the power with which SA works (P_{NOM}) and the list of possibilities for selecting a different power value from the vector P. Priorities of the SAs (pr) were also taken into account when modifying power settings. Priorities were set on a three-point scale: $EEM\_PRIORITY\_LOW$, $EEM\_PRIORITY\_MEDIUM$, and $EEM\_PRIORITY\_HIGH$. Such approaches have made it possible to determine which SAs should modify their power settings at the very end. In this way, user comfort or the technical requirements of a given device are taken into account. In previous works, the value of 0 was assumed for the ts parameter. Such an assumption meant that the operation of a given SA could not be postponed in time. The novelty presented in this article is the definition of the value of the ts parameter on the basis of the results obtained from the neural predicting model of PV RES.

3. Neural Predicting Model of PV RES

The Group Method of Data Handling (GMDH) neural networks and the regression method were used to build a neural predicting model for a PV system. The GMDH neural networks belong to the group of self-organizing networks [14]. Their greatest advantage in comparison to traditional neural networks is their ability to automatically create a network structure, which significantly shortens the time needed to obtain the final prediction result as well as enables the creation of an optimal network structure. The structure of the GMDH network is created automatically on the basis of prepared training and testing data sets. During the training process, the network grows and evolves as long as it leads to an improvement in its effectiveness [15]. Before the next layer of neurons is attached to the current network structure, the components of the new layer are selected for processing accuracy. Neurons that do not meet the condition imposed by the evaluation criterion (a processing error associated with neurons that are too large) are eliminated from the network structure. In addition to the above-mentioned advantages of the GMDH neural networks, they are also characterized by very good predicting properties, which have been presented, for example, in several papers [16–19].

A neural predicting model based on the GMDH neural networks was prepared for the purpose of predicting the power generated by a PV system. Initial research was carried out on the basis of a modified predicting algorithm developed by the author and presented in [20]. The input data for the GMDH neural network were created based on the methods presented in [21]. The basis for the preparation of input data for the GMDH neural network using the regression method was exemplary meteorological data showing the value of the irradiation of a photovoltaic panel within a given hour as well as the corresponding value of the power generated by RES. The authors assumed that in order to model RES, weather data collected at 15 min intervals would have to be used. The value of the time interval resulted from the need of the adopted neural predicting model for initial verification. Training data for the neural network were prepared for the entire month based on 15 min intervals. On the basis of such input data prepared for the neural network, the process of training and predicting the power value generated by the RES takes place. It was assumed that the predictions of the generated power would be made for the entire next day, that is, for 96 intervals of 15 min.

Figure 2 presents the obtained preliminary research results. The actual power generated by PV was compared with the power value (PV_{NN_GMDH}) predicted by a neural predicting model based on GMDH neural networks.

Good quality predictions were then obtained, which only differ slightly from the actual values of the power generated by RES. In order to better illustrate the obtained results, Figure 3 presents the residual values $\left(r\left(t_{pred}\right)\right)$, which are the differences between the predicted value of the power generated by RES $PV_{NN\_GMDH}\left(t_{pred}\right)$ and the value of $PV\left(t_{pred}\right)$ power generated by RES for the same moment (hour) of prediction, calculated using the following relation:

$$r\left(t_{pred}\right) = PV\left(t_{pred}\right) - PV_{NN\_GMDH}\left(t_{pred}\right) \quad (2)$$

On the basis of the calculated residuals (r), the values of selected prediction quality measures were determined: minimum and maximum values from the r residual, mean error (ME), absolute mean error (MAE), mean square error (MSE) with its components (MSE_1, MSE_2, MSE_3), and the root of mean square error ($RMSE$); these are presented in Table 1. The determined values of the residuals and the prediction quality measures constitute the basis for the evaluation of the obtained results.

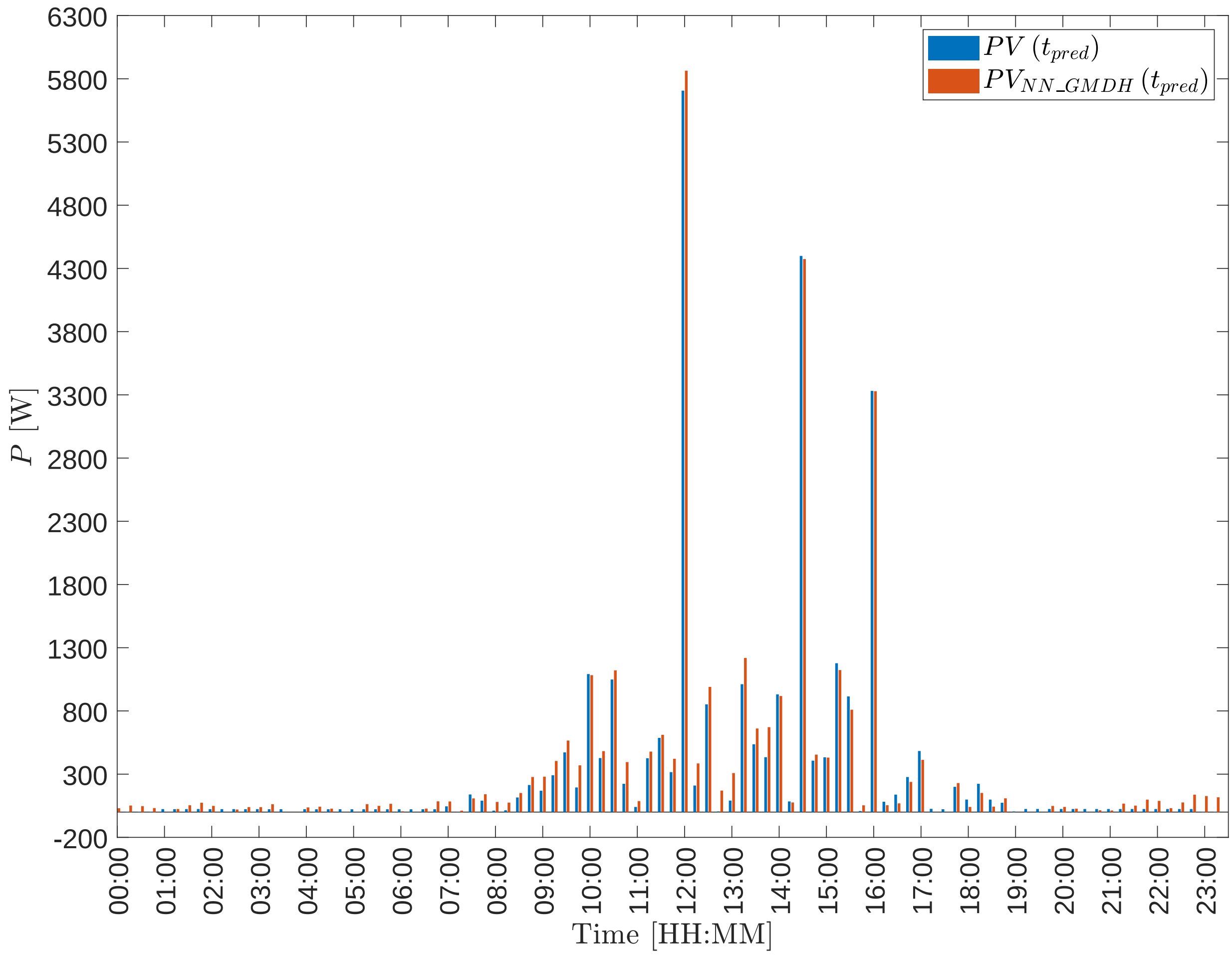


Figure 2. Power values generated by photovoltaic panels (PV) compared with the power value predicted by the neural predicting model (PV_{NN_GMDH}).

Table 1. The obtained values of the prediction quality measures for $PV\left(t_{pred}\right)$ and $PV_{NN\_GMDH}\left(t_{pred}\right)$.

Measure of Quality of Prediction	$PV\left(t_{pred}\right)$ and $PV_{NN\_GMDH}\left(t_{pred}\right)$
min[W]	−237.3
max[W]	105.1
ME[W]	−33.8
MAE[W]	53.9
$MSE\left[W^2\right]$	5651.1
$MSE_1\left[W^2\right]$	1141.8
$MSE_2\left[W^2\right]$	81.2
$MSE_3\left[W^2\right]$	4428.1
$RMSE$[W]	75.2

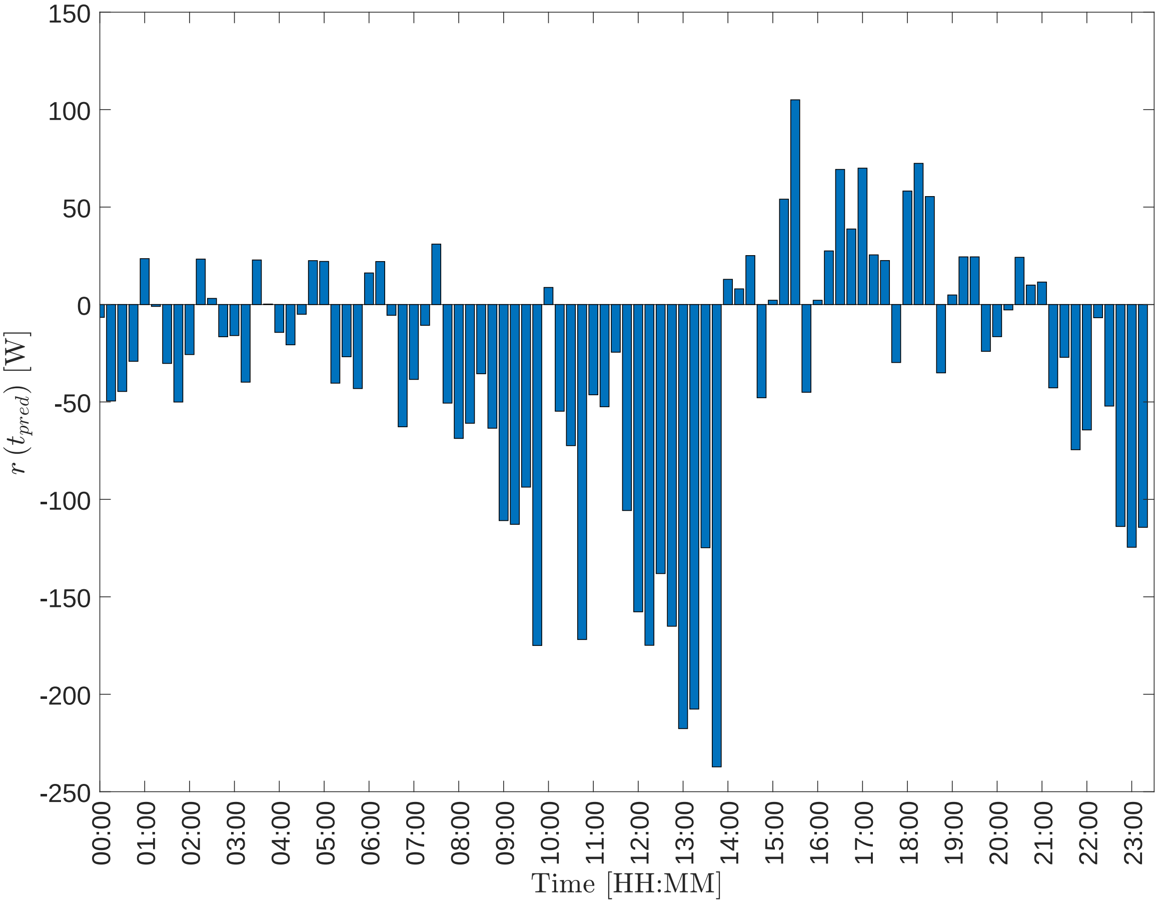


Figure 3. The obtained values of r residuals for predicting the power generated by RES in the form of photovoltaic panels.

The following conclusions were drawn from the presented research results (Figure 3) and Table 1:

1. All the obtained residual values are within the limit of ±237.3 W, which is a very good result. This is also confirmed by the obtained low values of prediction quality measures, for example, for MAE and $RMSE$.
2. The comparison of the ME, MAE, and MSE_1 value errors shows that the obtained predictions are loaded. The obtained predictions are underestimated (ME error values are negative).

3. There is a relatively small MSE_2 error for the obtained predictions of RES generated power. This implies a good prediction of the variability of the predicted values in relation to the variability of the observed values.
4. In the obtained results of predicted power generated by RES, there are cases of large residual values. These are caused by a poor fit of the model to the data of the power generated by RES. Hence, in the results of the prediction quality measures, there is a relatively high value of the MSE_3 error component.

The obtained results of the preliminary research show the good quality of the obtained predictions of the power generated by RES as well as the correct operation of the neural prediction model. The results of the predictions can be used for the effective management of the SA. Taking into account the small residual values obtained, it is then possible to control household appliances. This approach makes it possible to increase the use of the level of power generated by RES.

4. Simulation Research

On the basis of the values obtained for $PV_{NN\_GMDH}\left(t_{pred}\right)$ (Figure 2) with the use of the GMDH neural networks and the regression method, it then became possible to determine the scope of potentialities for when a given SA could be shifted in time (parameter ts from Formula (1)). By analyzing the $PV_{NN\_GMDH}\left(t_{pred}\right)$ values (Figure 2), assumptions were made for the ts parameter. Due to the PV generation, the activation times of individual SAs were selected so that the implementation of a particular activity by an SA would start and end at $t_{PV_{NN\_GMDH_1}} = 10{:}00$ and $t_{PV_{NN\_GMDH_2}} = 17{:}00$, respectively. An assumption also concerned the concentration of individual SA launches at: $t_{PV_{NN\_GMDH_3}} = 12{:}00$, $t_{PV_{NN\_GMDH_4}} = 14{:}30$, and $t_{PV_{NN\_GMDH_5}} = 16{:}00$. This assumption results from the fact that the PV system generates a large amount of power exceeding 3 kW.

For the purpose of simulation research, 15 SA devices were defined for an exemplary household. Figure 4 shows the start-up schedule of individual SAs in a single household and the value of the nominal power that is charged P_{NOM}.

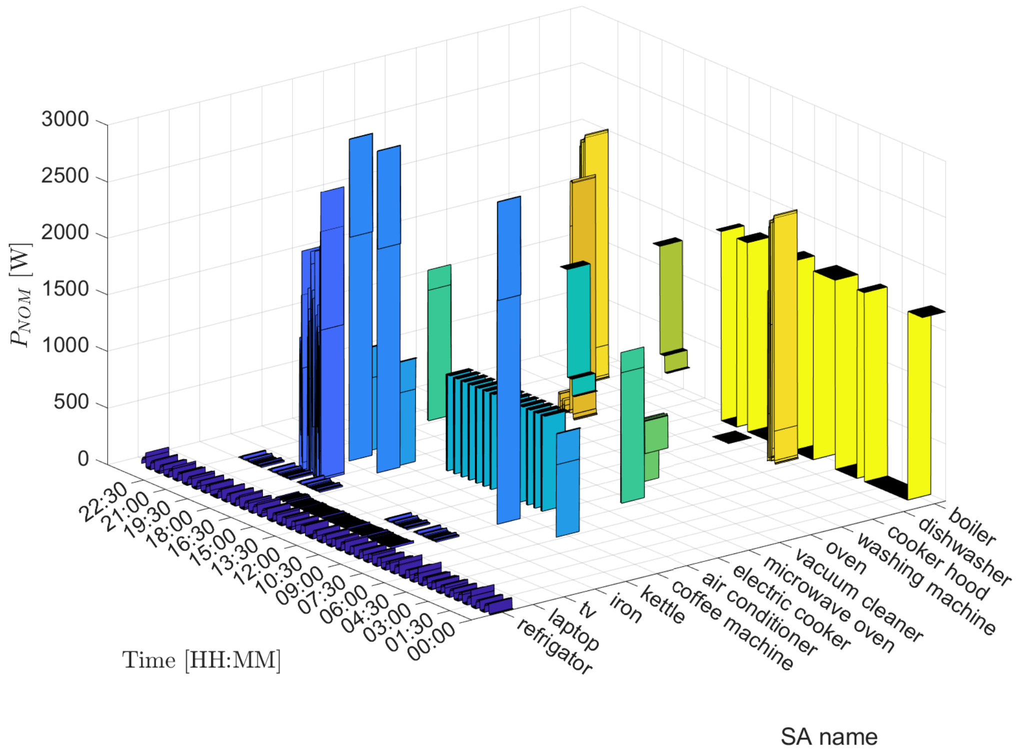


Figure 4. Schedule of the launch of individual SAs.

Among the defined SA devices, there are devices that are started periodically and aperiodically. An example of an SA that is run periodically is the refrigerator, and an aperiodic one is the coffee machine. The times of SA start-ups selected correspond to the daily activities carried out in an exemplary household during one day.

Figure 5 shows the sum of the SA power ($\sum P_{SA}$) that is needed to perform individual activities during the day.

Based on the analysis of the value $\sum P_{SA}$ from Figure 5, it can be concluded that the user carries out his/her activities throughout the day. In this case, there are only a few actions, and thus the starting SA devices are triggered within the time range from $t_{PV_{NN\_GMDH_1}}$ to $t_{PV_{NN\_GMDH_2}}$.

For a further part of the simulation research, we decided to modify the launch times of selected SAs using the *ts* parameter defined in Formula (1). In this case, a situation was considered in which the modification by the EEM algorithm would only affect the SAs and additionally, the user behavior. The change in the user's behavior is understood in this case as a shift in the time of performing an activity, e.g., vacuuming. Therefore, for the analysis, three simulation research scenarios (*sc*) were considered: the results without using the EEM algorithm (sc_1), the results using the EEM algorithm (sc_2), and the results using EEM with user behavior modification (sc_3). Figure 6 shows the $\sum P_{SA}$ values for all three *sc*.

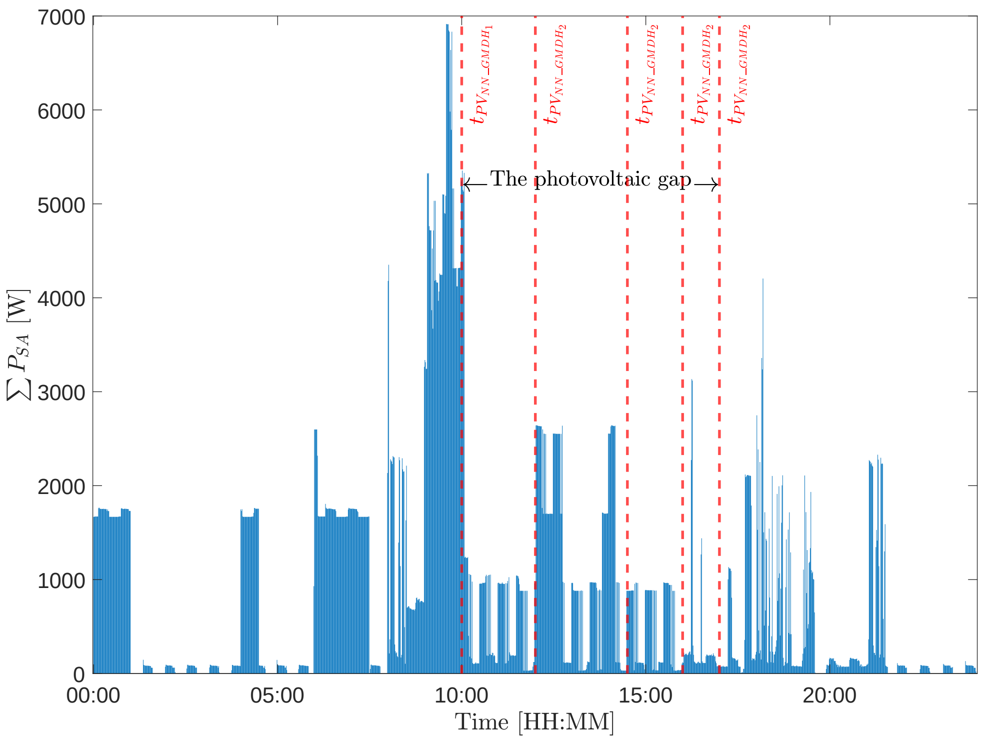


Figure 5. Total values of power consumption ($\sum P_{SA}$) by all devices.

Based on the value of $\sum P_{SA}$ from Figure 6, it can be concluded that the sc_2 variant in relation to sc_1 resulted in an increase in energy consumption in the range from $t_{PV_{NN\_GMDH_1}}$ to $t_{PV_{NN\_GMDH_2}}$. The biggest modification of activations of the selected SAs took place for sc_3. A detailed list of modifications performed by the EEM algorithm is presented in Table 2.

The top half of Table 2 lists the devices with the launch offset applied. The shift in time represents the earlier or later activation of a given SA. The washing machine start-up was brought forward by 5 h and 35 min. In contrast, the operation of the air conditioner was delayed by 3 h. In the case of the dishwasher, there was both a delay (postponing from 08:00 to 10:00) and a preparation of the activation (from 21:00 to 12:00). Modifications introduced by the EEM algorithm are comparable to a situation when the user sets a given device in automatic operation mode with a selectable and programmable start time. In this situation, the user's comfort of life does not deteriorate. The bottom half of Table 2 presents options for modifying the SA start time with the use of the EEM algorithm, which may already have a greater impact on user comfort. In this case, these SAs will have the highest priority $pr = EEM\_PRIORITY\_HIGH$ (Formula (1)), which will ensure that modifications are made only in the EEM_2 or EEM_3 variant. In the EEM_1 variant, such an action could only be imagined if the user, due to an incentive from the DSO (e.g., lower cost of electricity), changed his/her behavior. In this case, such a modification could consist in changing the time of meal preparation or changing household activities.

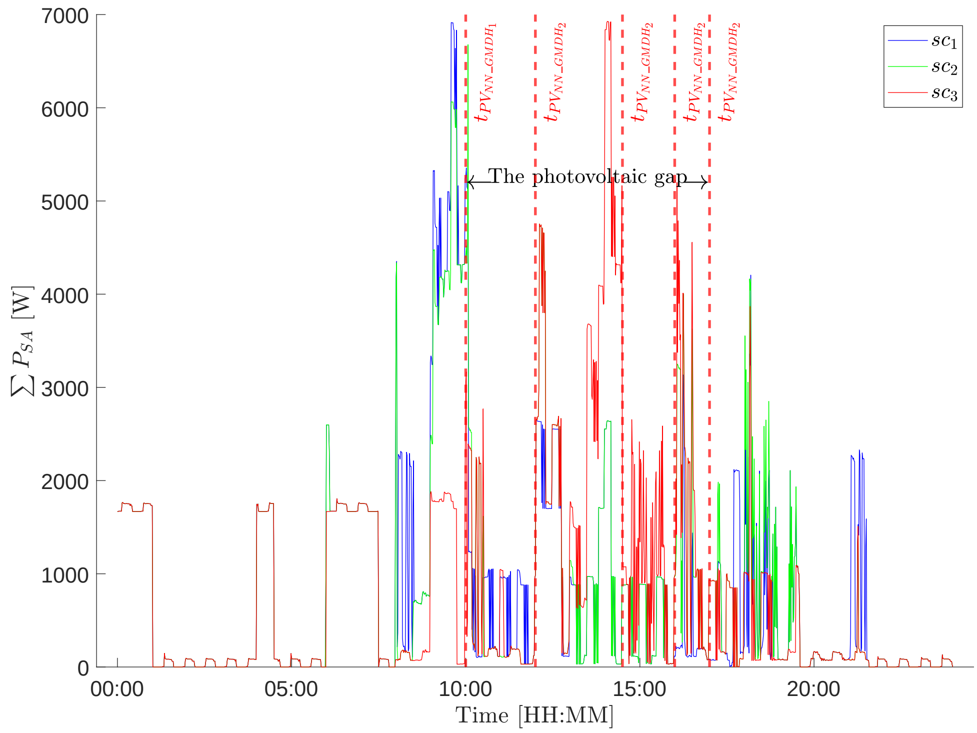


Figure 6. Compared power consumption ($\sum P_{SA}$) for three scenarios: without EEM (sc_1), with EEM (sc_2), and with EEM along with user behavior modification (sc_3).

Table 2. List of activation modifications for selected SAs by the EEM algorithm.

SA Name	Value of the *ts* Parameter for: sc_1	sc_2	sc_3	EEM Variants
washing machine	17:35	12:00		EEM_1
dishwasher	08:00	10:00		
	21:00	16:00		
air conditioner	09:00	12:00		
kettle	08:00		10:00	EEM_1 [1], EEM_2 and EEM_3
coffee machine	06:00		11:00	
	17:15		16:30	
microwave oven	08:00		10:30	
vacuum cleaner	08:30		13:00	
oven	09:05		13:30	
cooker hood	09:05		13:30	
iron	18:00		14:45	

[1] EEM_1 only with user consent.

5. Correlation of SA Operation Modification on the *ts* Parameter

In addition to preparing or postponing the SA startup, it is also possible to pause the execution in the EEM algorithm. It is not always possible or cost-effective to temporarily stop the device for design reasons. A pause could entail an increase in the cost of heating the water in devices such as the washing machine or the dishwasher. Sequentially, in Figure 7 and 8, the times when such a pause could occur are marked. The profiles were obtained based on the measurement of the device [22].

For the washing machine (Figure 8), there is a gap labeled gap # 1 between t_1 and t_2. Gap # 1 means the washing machine can be paused freely during this interval. There will be no additional energy costs for restoring the appliance to its pre-paused condition. In the case of the dishwasher (Figure 8), it is possible to pause the device only at certain times: t_1, t_2, and t_3. The individual times represent the end of the specified dishwashing cycle.

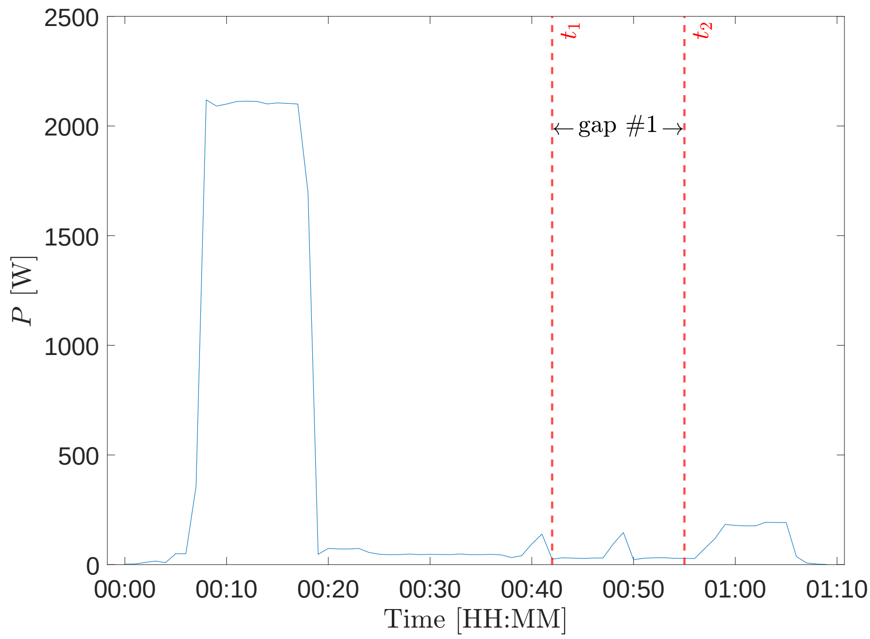


Figure 7. Profile of an exemplary washing machine.

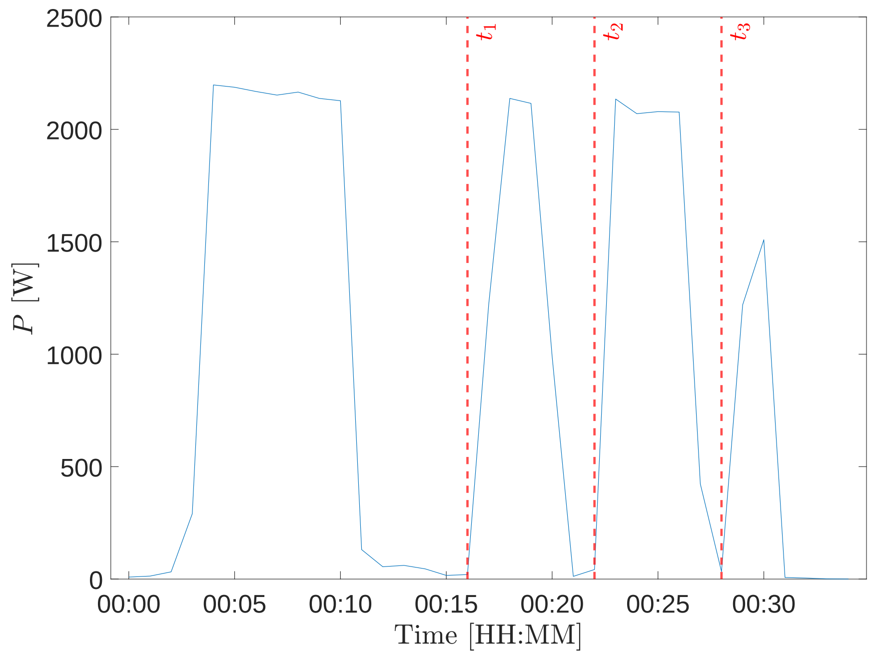


Figure 8. Profile of an exemplary dishwasher.

6. Simulations of SAs with Novel Functionality

The scenario for the operation of the EEM algorithm is as follows. The central unit with the EEM algorithm implemented collects information from the SG about readiness for operation and the provision of demand management services. For a selected group of SAs, the algorithm realizes their activation during a given time period. For example, for dishwashers, this will be for two hours in the morning, e.g., from 10:00 to 12:00. The simultaneous activation of all devices would put a significant load on the power grid. Therefore, the EEM algorithm randomizes the number of devices to be activated every minute without exceeding five devices. Then, the activation of a given number of devices will be quasi-evenly distributed over the given service period. If the status of readiness or non-readiness was sent by any of the devices during the period designated for the operation of the service, the algorithm would appropriately modify the number of randomly selected devices to be activated each minute.

The modification of the EEM algorithm operation presented in this article concerns the operation of SAs. These devices will have the ability to delay the activation and add a defined break in the operation (program pause), which will not affect the quality of the activity performed. To meet such requirements, the algorithm needs status information about the level of energy generated from RES systems, e.g., a PV system. It is the "$PV_{generation\ status}$" signal that reaches the value of "1" for high PV energy generation and is "0" for low or no PV generation. The level of the status signal should be selected individually for a given network. Generation of energy above the average load energy of a given line should set the status signal to the value "1". This procedure may be based on the measurements of both the generation power and the load power, as well as on the prediction of these signals. For the purpose of this article, this value is determined on the basis of measurements. The change of the status word is immediately sent by the central unit to the selected SAs that have not yet finished their work.

An example of the operation of the EEM algorithm for SA in the form of a dishwasher with new features (a pause in operation and a delay in switching on) will be presented in this section. In the numerical experiment, the operating profile of a dishwasher was adopted, as shown in Figure 8. The operation of the dishwasher is characterized by a multiple impulse consumption of high energy (about 2 kW) during the work cycle. For the purpose of this article, a simulation of a dishwasher with the load profile shown in Figure 8 was performed, with a break in operation after the first cycle of work (time t_1), resulting from the completion of pre-washing. The operation of the dishwasher is divided into two stages. These stages can be consecutive without delay or separated by a break. The mode of operation will depend on the level of power generated by the PV system.

The following operating scenarios may occur for a dishwasher, as shown in Figure 9. Figure 9a shows that the dishwasher is activated when the "$PV_{generation\ status}$" signal is equal to "1". Then, the first stage of the dishwasher's operation (period $t_{on\ 1} - t_{off\ 1}$) starts. The first stage of operation also ends when the "$PV_{generation\ status}$" signal is "1", although it turns to zero while the dishwasher is running. Therefore, upon completion of the first stage, the dishwasher is immediately started for stage 2 (period $t_{on\ 2} - t_{off\ 2}$).

In the second operating scenario for the dishwasher, Figure 9b, the dishwasher is activated when the signal "$PV_{status\ generation}$" is equal to "1", and the first step of operation ends when the signal "$PV_{status\ generation}$" is equal to "0". However, the device does not continue its program operation until a "1" signal is encountered (period $t_{on\ 2} - t_{off\ 2}$). There is a pause in the operation of the dishwasher due to the lack of solar power generation. This will cause the consumption of energy from renewable sources to increase.

The third operating scenario (Figure 9c) is similar to the second operating scenario. The difference is that dishwasher is activated when the signal "$PV_{status\ generation}$" is "0". Thus, the actual activation of the dishwasher operation occurs when the signal "$PV_{status\ generation}$" changes its state to "1". There is a delay (t_{delay}) in turning on the device due to the device activation signal. Then, the operation of the device is determined by the completion of step 1 and the value of the $PV_{status\ generation}$ signal. In the example in Figure 9c, the operation of the device is paused, as in scenario 2.

Basing the operation of the SA on the status signal of the operation of energy generation systems has some disadvantages. These disadvantages result from the fact that the generation of energy by RES systems is not predicted. Such an approach may lead to a given SA being turned on just before the end of high generation from RES, while its operation might occur when there is no energy generation. An example of such a scenario is shown in Figure 9d. Therefore, a more complete and improved function of the proposed EEM algorithm executed together with a new SA functionality can be achieved by using RES generation prediction algorithms. However, the prediction of RES generation is not the main topic of this article. We thus indicate here the necessity to apply and present one of the possible algorithms for predicting energy generation from RES.

The operation of the EEM algorithm increasing the consumption of electricity during the generation of energy by the photovoltaic system is shown in Figure 10. This algorithm has been designed to maximize the consumption of electricity generated by PV with the use of smart home appliances. In the analyzed verification example, only the dishwashers were used. The algorithm had 100 permanently defined devices that participated in the provision of the demand response service. The load profile was the same for each of the dishwashers. The results shown in Figure 10 are for two variants; one made use of the classic dishwasher profile (in the EEM algorithm ts = 0, for all SAs $-$ EEM_{ts_const}) [7,11] and the other, the modified dishwasher profile described in Figure 9 (EEM algorithm with variable values for the parameter ts, for all SAs $-$ $EEM_{ts\_variables}$). The obtained results for a PV system with a profile of energy generation that is highly variable in time are shown so as to highlight the advantages of the proposed approach. The power grid load profile (green curve at the bottom of Figure 10) was increased by the operation of 100 dishwashers. The proposed EEM algorithm randomly selected the number of devices to be activated every minute. For this example, a maximum of three dishwashers were turned on at any given minute. By using EEM_{ts_const}, a more even distribution of the generated load was obtained as additional dishwashers were turned on. On the other hand, the use of $EEM_{ts\_variables}$ resulted in a more variable load profile, with the energy consumption being higher during the state when a large amount of energy was being generated by the PV system (signal "$PV_{status\ generation}$"). The analysis showed that 10,614.00 W less energy was taken from the grid for $EEM_{ts\_variables}$ as compared to EEM_{ts_const}. Since one dishwasher consumes 564.7 Wh of energy in a single work cycle, the saved energy would be enough for about 19 (exactly 18.79) cycles of the dishwasher with the tested profile. This means that the consumption of energy generated by the PV is increased by 19%. The dishwasher has a fairly extensive washing program sequence (Figure 8). There are four peaks in energy consumption. If its program of operation was divided into four stages, then even more satisfactory results from the EEM algorithm could be achieved.

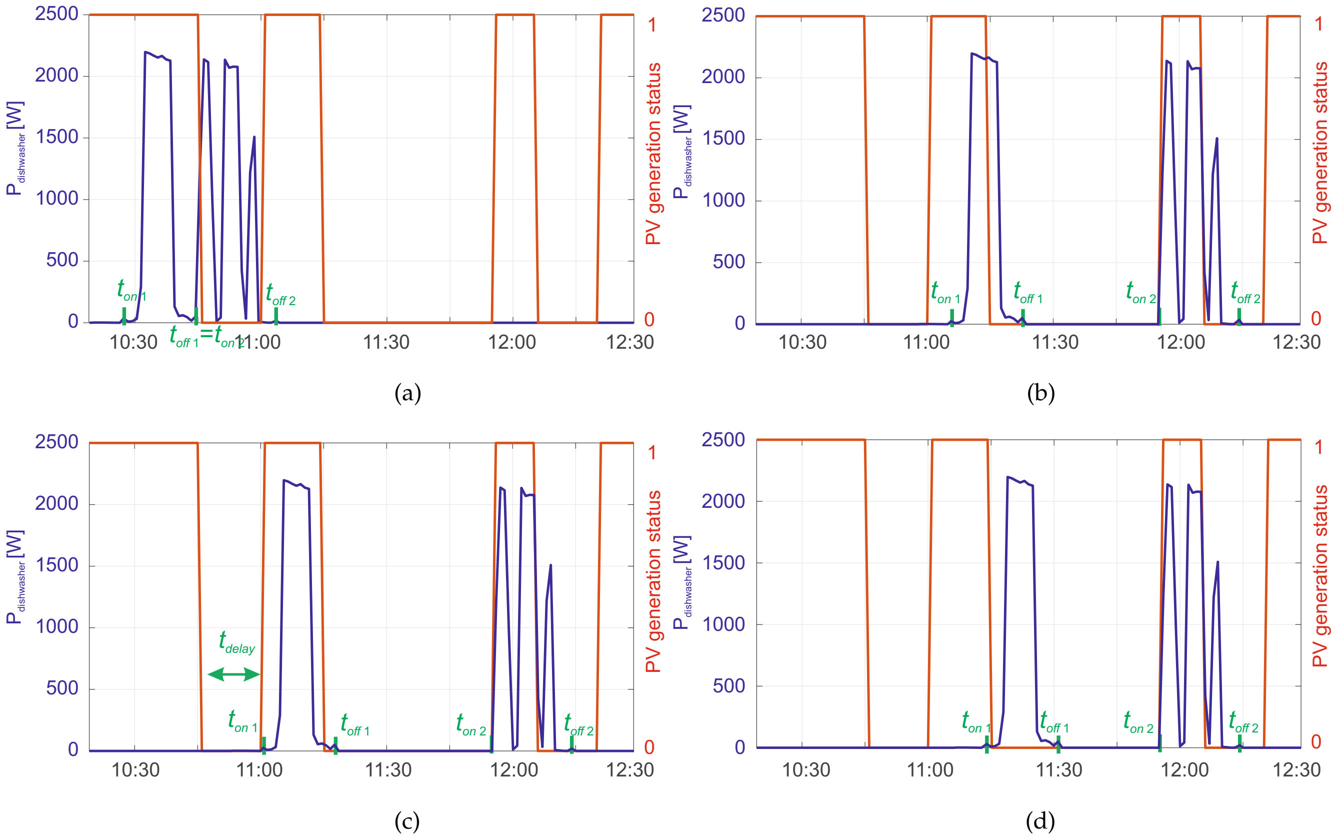


Figure 9. Examples of dishwasher operation with a pause in its operation due to the EEM algorithm: (**a**) without a pause in operation, (**b**) without a delay in switching on and with a pause in operation, (**c**) with a delay in switching on and with a pause in operation, (**d**) without a delay in switching on and with a pause in operation. The moment of switching on occurs just before the end of the PV generation.

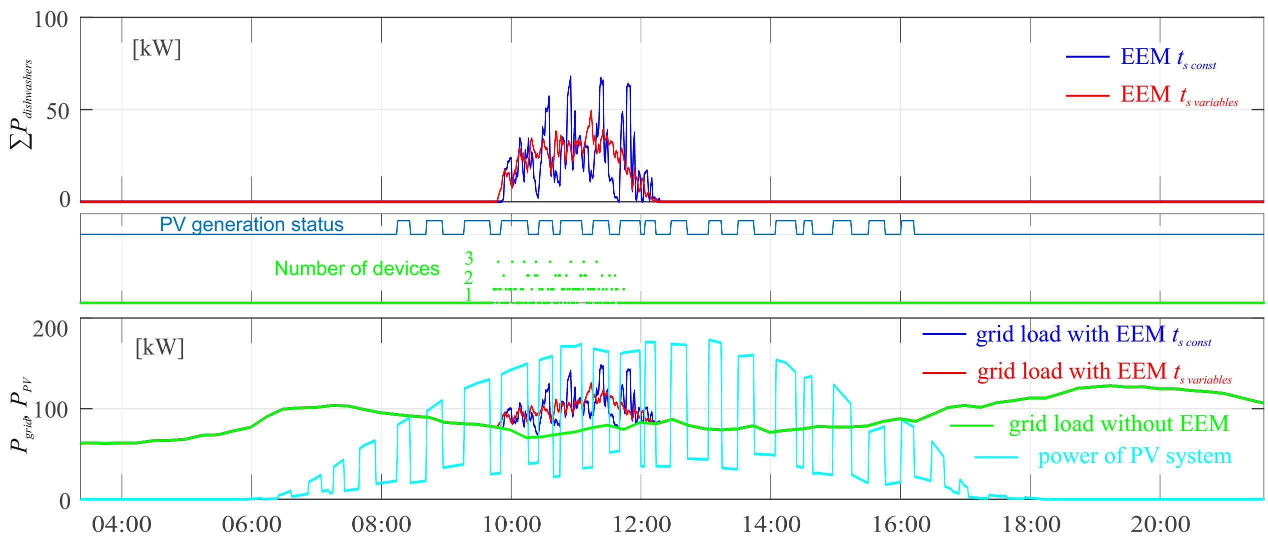


Figure 10. Numerical experiment of electric power systems with PV installation and the elastic energy management algorithm for 100 dishwashers.

An operation similar to that of the dishwasher was performed for the washing machine, with its energy consumption profile shown in Figure 7. The washing machine operation was also split into two stages, with an operation pause at t_1. Since the washing machine has one power consumption peak associated with heating the main wash water, it should be expected that the increase in energy consumption from PV systems will be less than in the case of using dishwashers. The main operation is when the washing machine is delayed as there is no high PV generation during this period. The obtained results from the numerical experiment of the EEM algorithm operation with the use of 100 washing machines are shown in Figure 11. Since one washing machine consumes 444.7 Wh of energy in one work cycle, the saved energy would be enough for about 4 (exactly 3.97) operations of the washing machine with the tested profile.

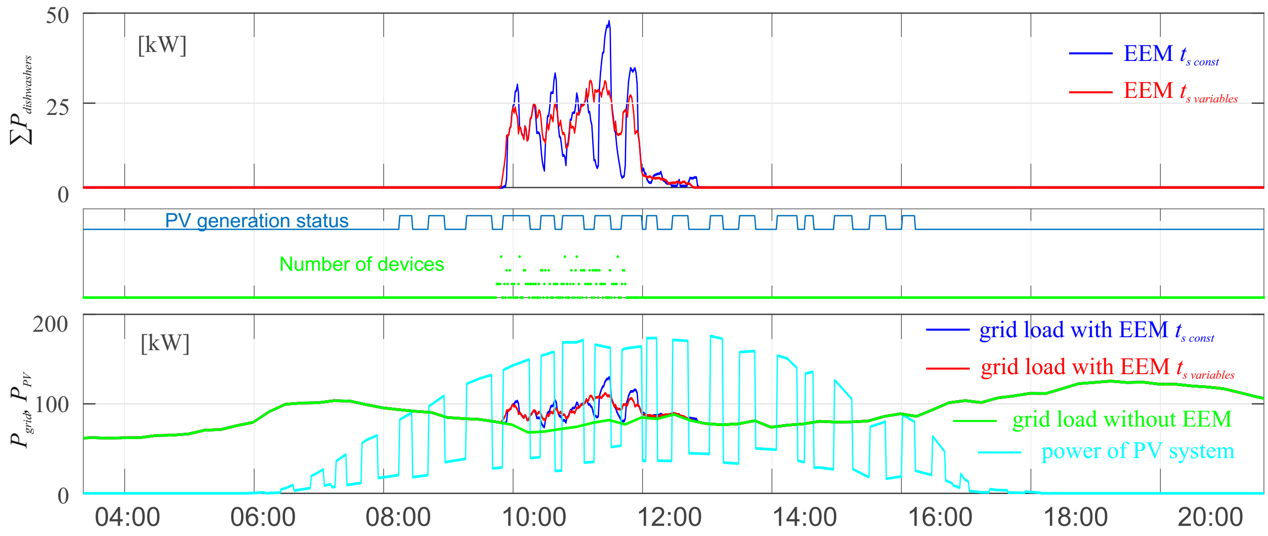
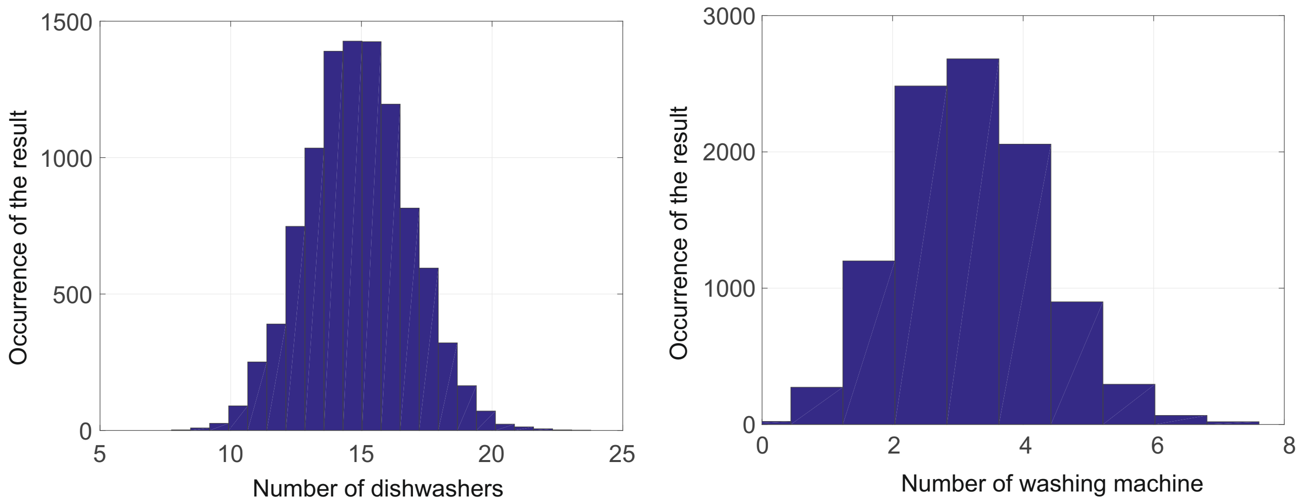


Figure 11. Numerical experiment of electric power systems with PV installation and the elastic energy management algorithm for 100 washing machines.

In order to illustrate the possible increase in electricity consumption from PV, a histogram was determined for 10,000 repetitions of the algorithm operation for the same generation profile (Figure 12). This histogram shows how many more dishwashers or washing machines were powered by PV energy with the use of the novel EEM algorithm as compared to the classic EEM. As can be seen, it is usually 14–16 dishwashers and 3–5 washing machines.



(a) (b)

Figure 12. Histogram showing the comparison of EEM_{ts_const} with $EEM_{ts\_variables}$ at 10,000 repetitions of the algorithm for: (**a**) dishwasher, (**b**) washing machine.

The presented research results show that in order to maximize the consumption of energy generated from RES, not only should the functioning of SAs be changed, but also the behavior of energy users. Research on changes in the behavior of energy users in this context has been the subject of many studies, including [23]. There are also many articles that propose solutions similar to those proposed in the present work. This article was not intended to review or compare the different energy management methods. As a work on a similar subject, the article [24] can be cited. It proposes an energy management system that automatically manages a smart home's energy demand according to network constraints and user priorities. The proposed system as well as the one proposed in this article are based on a heuristic technique. The energy management method takes into account the user's priorities and the power available from the power system and RES. The limitation of this approach is its complication related to the need to obtain information regarding the power available from the grid and the power generated from RES. Acquiring information about renewable energy generation is also a problem in the approach proposed in this article. Therefore, the prediction of energy production from renewable energy sources is an essential issue for further research.

7. Conclusions

Energy management is an important issue in national power systems. In particular, it is about the volatility of supply and demand for electricity. Earlier works have confirmed that the EEM algorithm makes it possible to achieve equilibrium under variable conditions of energy demand, which occur, among others, for renewable energy sources. It is also possible to react to the appearance of the peak demand phenomenon.

The article presents the results of our research, which constitute an extension to the previous work on the EEM algorithm. The results concerned the impact of the *ts* parameter on the possibility of modifying the operation of smart appliance devices. In this case, the shift in the operation or the acceleration of SA devices was considered. This article analyzed the separation of the work profile of intelligent devices into two stages. This approach resulted in an additional increase in SA's use of energy produced by PV generation.

The new SA functionality proposed in this article concerns postponing the activation of a given SA and dividing the work profile into stages, if this is possible. Such SA functionality requires the EEM management algorithm to deliver to the SA not only commands to operate, but also status information on the presence of high energy generation from RES installations. This complicates the operation of the proposed algorithm as well as significantly increases the amount of data transferred.

Furthermore, obtaining satisfactory results must be related to the prediction of electricity generation from RES installations. Therefore, this article indicated this problem and discussed one of the possible prediction methods based on the GMDH neural networks and the regression method. However, the prediction of energy generation is not the main topic of the article. In being able to approximate the the level of potential energy generation, it will then be possible to delay the operation of an SA if the short-term forecast of 5–10 min indicates a lack of energy generation.

The operation of energy demand management algorithms will also affect the user's comfort. These algorithms can extend the implementation of certain tasks, such as washing clothes, washing dishes, etc. In the case of no energy generation from RES systems, the execution of the task should be limited to a satisfactory time period—for example, extend the washing of clothes by a maximum of one hour compared to the standard program. The deterioration of the comfort of use will also be associated with the need to prepare SAs in advance and for tasks to be performed either in the evening or in the morning. However, the benefits of energy independence and the reduction of electricity costs will compensate for the inconvenience. This is even more important as energy prices have risen significantly recently as a result of geopolitical turmoil. The ecological aspects that contribute to increasing the use of energy coming from renewable sources are also important. Additionally, the operating parameters of the power system are improving; this reduces the level of generation and load mismatch, which directly translates into a reduction in network voltage fluctuations.

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Abbreviations

The following abbreviations are used in this manuscript:

$\sum P_{SA}$	Sum of the SAs power
COP21	Paris Climate Conference
DCD	Distributed control devices
DSO	Distribution System Operator
EEM	Elastic Energy Management
EEM_1, EEM_2, EEM_3	Three variants of the EEM algorithm
EEM_{ts_const}	Designation in the EEM algorithm ts = 0, for all SAs
$EEM_{ts\_variables}$	Designation in EEM algorithm with variable values for the parameter ts, for all SAs
ESS	Energy storage systems
EU	The European Union
GMDH	Group Method of Data Handling
GRASP	Greedy Randomized Adaptive Search Procedure
MAE	Absolute mean error
MSE	Mean square error with its components (MSE_1, MSE_2, MSE_3)
NPS	National Power System
P_{NOM}	A list of possibilities for selecting a different power value from the vector P
pr	Priorities of SAs
PV	Photovoltaic systems
$PV_{generationstatus}$	Activation tags
PV_{NN_GMDH}	Predicted power value
$r\left(t_{pred}\right)$	Residual values
RED II	Renewable Energy Directive
RES	Renewable energy sources
$RMSE$	The root of mean square error
SA	Smart appliance
sc	Simulation research scenarios
SG	Smart Grid
t	Time stamps
TSO	Transmission system operators

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