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Intelligent Electric Power Management System for Economic Maximization in a Residential Prosumer Unit

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ABSTRACT The electricity demand has grown continuously in recent years, raising the necessity to expand generation sources, distribution networks, and equipment efficiency. In addition, it is necessary to attend sustainable development in a conciliated manner. Applications involving the intelligent management of the distributed networks have increased to achieve a balance between growth and sustainability. In this context, this article presents the development of an Intelligent Electric Power Management System (IEPMS) for the economic maximisation of a photovoltaic system applied to a prosumer residential unit without storage in Brazil. Using historical meteorological data and a heuristic to simulate energy use habits, the IEPMS forecasts both generation and demand in 24 hours. From the projections, an optimisation problem was built and solved using the genetic algorithm technique to find the most economical moments for driving loads. This model aims to reach the lowest daily cost of electricity, considering the return (sale) of unused energy to the power distribution company. The validation of the IEPMS considered four usage patterns, integrating 26 scenarios, those composed by the (i) flexibility; (ii) type of tariff; and (iii) hit rates provided by the climate forecasting method proposed for the system. As a result, the IEPMS savings considering the white tariff were 34.72% for one year, assuming full-time external work usage. Additionally, it was possible to identify in all scenarios that the proposed method's performance was not less than 97%, measured through the relative error among distinct hit rates of the evaluated climatic forecast.

INDEX TERMS Smart grid, electric power management, intelligent systems, residential prosumer unit, energy management systems.

NOMENCLATURE

PARAMETERS

A	area of the PV arrangement m^2
CI	clearness index
CP_{temp}	temperature coefficient for maximum potency %/°C
DBT	dry bulb temperature °C
$D+1$	next day
$\$E_{com_k}$	cost of energy sold in period k R\$
Ef_{inv}	the average efficiency of a photovoltaic inverter %
Ef_{mod}	the average efficiency of a photovoltaic module %
E_{hour}	energy generated per hour kWh
f	final
$Flex$	flexibility of temporal allocation of a load
GHR	global horizontal radiation kWh/m^2
i	initial
k	discrete sample for the time window
$Losses$	system losses %
OPT	operation time min
P_{com_k}	power traded in period k kW
P_{ger_k}	potency generated in period k kW
$P_{i,k}$	instantaneous potency of load i in period k kW
P_{inst_k}	total instantaneous potency in period k kW
POF	probability of occurrence function
P_{peak}	photovoltaic power installed under the standard test conditions W

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P_{PV}	installed PV power corrected according to ambient temperature W
$RMSE$	root mean square error
Δt	minimum operation time min
∂	load duration, multiple of Δt
γ	multiple of Δt over one day
$\$Day$	daily energy cost R$
$\$TE$	cost of the instant energy fare R$

ABBREVIATIONS

ANEEL	National energy agency of Brazil
ANFIS	Adaptive neuro-fuzzy inference system
BSS	Battery storage system
COPEL	*Companhia paranaense de energia* COPEL-DIS *COPEL Distribuição S.A.*
DERs	Distributed energy resources
DG	Distributed Generation
DSM	Demand-side management
ELM	Extreme learning machine
EMS	Energy management system
IEG	Intelligent electric grid
IEPMS	Electric power management system
LabEEE	Building energy efficiency laboratory
MINLP	Mixed-integer nonlinear programming
MLP-NN	Multilayer perceptron neural network
MPC	Model predictive control
PAPAR	Peak-to-average power ration
PMG	Prosumer micro-grids
PSO	Particle swarm optimisation
PU	Prosumer unit
PV	Photovoltaic
UFSC	Federal University of Santa Catarina
TE	Energy tariffs
TUSD	Tariffs for the use of the distribution system

I. INTRODUCTION

The demand for electrical energy has increased during the last years, bringing on the need to find new electrical energy generation sources or improve the existing electrical energy sources with smart grids and efficient equipment. Additionally, this growth must respect sustainable development concepts since traditional electrical energy generation sources use finite resources. Recent studies present that intelligent distributed smart grids are a potential solution to increase the electrical energy system's trustworthiness and quality while decreasing the risk of blackouts or problems due to electricity shortages [1]. To emphasise this idea, the research presented in [2] stated that artificial intelligence can be used to automate human actions and/or decisions to optimise power consumption and production.

The recent evolution of electrical energy generation technologies allows the development and integration of solutions that bring benefits like energy-saving and sustainable use. According to [3], the present form's electricity grid is unreliable, provides considerable transmission losses, has poor power quality, and discourages integrating distributed energy sources. On the other hand, public incentives, prices more attractive, and rapid installation must speed up the application and use of photovoltaic systems around the world [4]. According to ANEEL – National energy agency of Brazil [5], there are currently around 170,000 distributed photovoltaic generators in Brazil. Figure 1 presents the projection from ANEEL, showing the total installed potency in Distributed Generation (DG) for the following years in Brazil [6]. This scenery presents a new appeal, identified by a neologism: the energy prosumer (electricity consumer and producer).

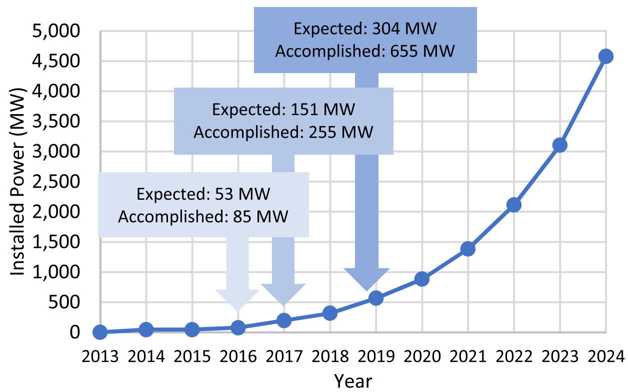

FIGURE 1. Projections for distributed generation in Brazil until 2024. Adapted from [7].

Unlike traditional grids, where electricity generally flows from generators to consumers, in a distributed network of prosumers, the energy flows in a bidirectional way and can vary in magnitude and direction [7]. Prosumers' distributed network will reduce the overload and the necessity to extend traditional and centralised electric systems. Nevertheless, there is still a demand to minimise consumption and losses.

Solar radiation is an intermittent energy source, and weather forecasting methods capable of monitoring variables related to solar energy conversion could be considered for energy generation of photovoltaic systems to allocate the loads properly. Machine learning techniques as Extreme Learning Machine (ELM) [8] and Random Forest [9] are being assumed to deal with historical weather data focusing on generating photovoltaic generation profiles, those known as Clearness Index (CI) [10], to minimise uncertainties of photovoltaic generation in an intelligent way.

A recent survey about demand management focusing on classification and review of existing demand-side management (DSM) systems was presented in [11]. The study also reported the most explored performance metrics related to energy management in the smart grid, showing that centralised and decentralised generation, consumer privacy, consumer preference, priority and satisfaction, peak-to-average power ratio (PAPR), cost minimisation, and the use of distributed energy resources (DERs) are the relevant topics in this area. To conclude, directions for future research are presented, and load profile modelling and consumers' participation in the scheduling algorithms, topics treated in the present research, are emphasised.

In the research in [12], a method to determine the optimal planning associated with a Photovoltaic (PV) unit and energy storage system is presented. The optimal operation is determined based on three values of the amount of charge at midnight on a sunny day, cloudy day, and rainy day to minimise the household's annual cost. Experimental data collected from 2 years were used during the validation of the proposed method.

A methodology to formulate a hybrid renewable energy system is addressed in [13], where the modelling procedures of components as PV panels, wind turbines, and lead-acid batteries are presented. Additional to renewable sources, the method also considered a diesel generator. Weather forecasting was assumed to define the power management strategies from both the demand-side and generation-side to meet the electricity demand while minimising the overall operating and environmental costs. Finally, the receding horizon optimisation strategy was assumed to solve the problem considering weather data to deal with PV generation uncertainties.

Recent research involving microgrid generation and load scheduling to increase the system's efficiency is presented chronologically in this work sequence. In [14], consumers' preferences, priorities, ease of use, grid stability, deviation minimisation, demand curve flattening, and implantation cost were assumed in a single management system. Based on a heuristic optimisation, authors acquired information from several sources (utility, weather, user preference, user budget limit, etc.) to augment energy use and budget by avoiding energy usage during periods of higher prices.

Considering the challenges involving uncertainties caused by intermittent renewable energy and random loads while optimizing multiple objectives involving economic and environmental aspects associate with microgrid scheduling of energy supply and demand, the work presented in [15] presented comparative experiments focusing on industrial customers. The study presented the formulation of a minimax multi-objective optimisation model to seek the minimum operating costs and emissions under the worst-case realisation of uncertainties. Additionally, a model transformation was performed to deal with strong coupling and nonlinearity in the proposed formulation. Finally, the Multi-Objective Cross-Entropy algorithm was adopted to solve the problem, showing that the model can effectively attenuate the disturbances of uncertainties and achieve optimal economic and environmental benefits.

One approach to enhance electrical energy use is through real-time consumption tracking coupled with the automatic triggering of schedulable loads [16]. The previously cited study presented the performance of a modified version of the Differential Evolution (DE) method, including a stochastic selection on a large-scale energy resource management problem with uncertainty associated with both load scheduling and weather conditions. The microgrid comprises a 25-bus residential area, including DERs, electric vehicles, and demand response programs. The problem formulation was used in the competition of the Congress on Evolutionary Computation in 2018.

A parallel optimisation approach assuming a problem formulation based on a real case was presented in [17]. The research assumed a genetic algorithm to improve the demand response to decrease the grid operation costs. In the sequence, the demand response was adjusted, assuming linear programming to decrease direct prosumer costs. The impact on the grid was evaluated, showing better grid management of the proposed strategy.

Based on the premise that peak power consumption is one of the most critical issues for power system operation and sustainability, in [18], a unified DSM model was presented involving multiple objectives. The minimisation of the electricity cost, the curtail peak hour's demand, PAPAR, and distribution losses were considered in the problem formulation where an integer linear programming solver was assumed. The results showed that the model could take care of a considerable number of DSM features, emphasizing the importance of heterogeneous load, load shedding, human interaction, peak clipping, valley filling, load sifting, appliances priorities, and consumer preferences.

In the same line of the prediction presented in this research, in [19], a day-ahead optimisation scheduling was presented. Assuming the Particle Swarm Optimization (PSO) method, the proposed optimisation scheduling algorithm showed efficiency in reducing the power supply pressure during peak load periods and effectively improving the microgrid's overall benefit. Moreover, the study focused on an islanded microgrid, where the proposed model was oriented to frequency regulation.

Assuming a generalized approach focusing on developing a joint energy management and energy trading framework, in [20], the minimisation of the power system's electricity cost is proposed considering various factors that influence the power system stability and sustainability. In this case, consumer load profile, load shedding, heterogenous load, peak clipping, valley filling, human interaction, appliances priority, and consumer preferences to maximize the use of distributed energy resources. Finally, integer linear programming was assumed to solve the proposed optimisation problem.

A similar approach to the one presented in this study, without physical implementation, was addressed in [21]. By performing day-ahead self-scheduling and weather and load forecasting, the study proposed an ensemble machine learning algorithm considering the adaptive neuro-fuzzy inference system (ANFIS) and the multilayer perceptron neural network (MLP-NN) for the prediction of weather variables. The proposed energy management system (EMS) considered the demand response based on forecasting data and the battery storage system's degradation cost (BSS) to provide an appropriate microgrid system's operation cost.

In prosumer micro-grids (PMGs), renewable energy sources' uncertainties are considerable challenges for the optimal day-ahead prediction. A probabilistic method for optimal scheduling and operation of PMGs was presented in [22] to solve this problem. Monte Carlo Simulations (MCS) was assumed for scenarios simplification. Moreover, k-means, k-medoids, and an evolutionary algorithm were compared to cluster the scenarios. Results showed that the k-medoids method performed better under various conditions.

Assuming a model predictive control (MPC) scheme for photovoltaic units' efficient energy management, in [23], the MPC controller was said to minimise aggregate prosumers' economic cost into a prediction horizon considering the generation forecasting. The method was compared with a heuristic strategy without considering prediction, showing that the MPC control provided cost savings. Finally, when a storage system was considered, the study reported that knowledge about future demand ensures cost saving for the proposed simplified scenarios.

Therefore, this article presents the development of an Intelligent Electric Power Management System (IEPMS) for economic maximisation in an energy prosumer residential unit in Brazil. Using historical meteorological data and heuristic on residents' energy use habits, IEPMS forecasts generation, and demand for the next 24-hour period ($D+1$). From the projections to produce photovoltaic energy (without storage) and the residential energy demand in ($D+1$), an optimisation model is assembled and solved using genetic algorithm techniques, which finds the most economical moments for driving loads.

This research contributes to the energy sector creating a solution to improve a prosumer unit's efficiency, considering simultaneously information from the electrical energy generation and lifestyle consumer to define the most suitable home activities scheduling. Additionally, according to the Ministry of Mines and Energy report [24], the number of prosumers increases for the following years. The technological solutions help consumer decision-making extract the solar system's maximum benefits since PV systems' efficiency is not satisfactory yet [25]. The solar energy prosumer seeks to extract the best efficiency of their electric systems, energetically and economically, without batteries.

The Intelligent Electric Power Management System (IEPMS) proposed in this work presents an opportunity to improve energy prosumer units' energy efficiency in residential, commercial, or industrial applications. This work brings experimental results of a residential prosumer unit to validate the proposed method. Additionally, a weather database is assumed to allocate the loads when the forecasting method's hit rate is 100%. For different hit rates of 95%, 90%, and 85%, a pseudo-forecasting method assumes daily historical weather of the next days to allocate the prosumer unit loads. This strategy is assumed to deal with the uncertainties associated with climate conditions.

Table 1 shows how this research fits when compared to recent research in the intelligent management of energy sources. As it can be verified, research works that were

TABLE 1. Schedulable loads and their operating window.

Reference	Without storage system	Weather forecasting	Energy sources uncertainties	Physical implementation or validation
[12]		x		x
[13]		x	x	
[14]	x	x		
[15]			x	
[16]			x	
[17]	x			x
[18]	x			
[19]	x			
[20]				
[21]		x	x	
[22]			x	
[23]		x	x	
This research	x	x	x	x

previously reviewed in this section were classified considering those without energy storage systems, that assume any strategy for weather variables forecasting; the studies that propose strategies to deal with climatic variables uncertainties, and finally, the ones that included the physical implementation of the energy management system or validation with experimental data. In this way, the scientific contribution of this work can be stated as:

- The proposed method presents a new simplified strategy for weather variables forecasting, those associated with PV generation.
- The weather prediction includes a hit-rate analysis to deal with uncertainties associated with the energy source.
- A physical implementation of the energy management system allowed the presentation of an actual energy usage pattern.

This article is organised as follows. Section II addresses the study and concepts related to energy prosumers and energy management systems. Section III presents the architecture of the proposed IEPMS. Section IV shows the practical application of the system and the parameters adopted for the optimisation process. In Section V, the results are presented and discussed. Finally, Section VI contains the conclusions derived from this research.

II. MATERIAL AND METHODS

Among the main topics discussed in this work, we can highlight the energy prosumer and the relation with the residential EMS.

A. THE PROSUMER CONCEPT

The integration of renewable energy sources into conventional energy grids challenges operators and planners. Currently, renewable energy systems have an innovative character, particularly the solar photovoltaic system, a clean energy resource [26].

Unlike traditional energy systems like hydroelectric and thermoelectric plants, where energy can be dispatched according to demand, renewable sources (solar and wind energy) are hard to store and dispatch. Additionally, renewable energy source generation has a significant variation in the function of the climate conditions [27]. While there are no reasonable and efficacious storage systems available in Brazil, the best energetic-financial solution is to consume the energy at the same instant it is produced, in a way named instantaneous consumption. The electric grid needs large quantities of conventional backup energy and ample energy storage [28] to allow a more significant proportion of renewable energy accommodation. Figure 2 illustrates a prosumer unit architecture.

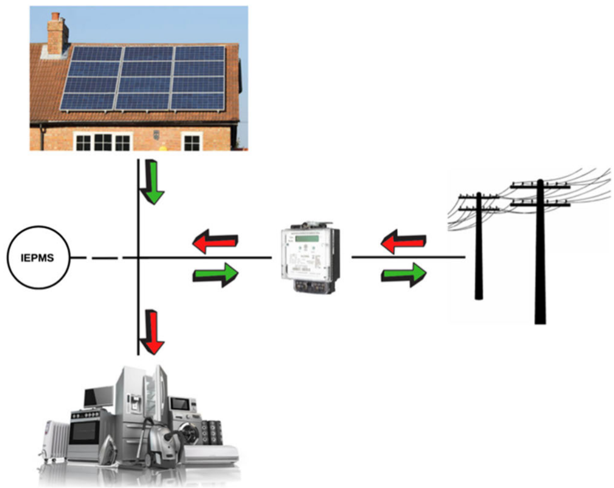

FIGURE 2. Power in a prosumer unit, without storage, controlled by the IEPMS (adapted from [31]).

The Intelligent Electric Grid (IEG) operates under a specific set of requirements, those presented in [29] and [30], namely: (i) Autonomous operation without energy dependence on external electric grids; (ii) Operation with equitable generation-consumption balance; (iii) Possibility of energy storage; (iv) Predominant use of renewable energy sources; (v) Ability to service non-traditional loads; (vi) New type of grid protection allowing a bidirectional energy flow; (vii) Active demand management.

B. ENERGY MANAGEMENT SYSTEM

Energy management systems (EMS) are an essential tool for automating demand management. Currently, financial incentives are the main factor that motivates users to adopt load control systems [32]. Energy management is a complex task, as the dynamics of energy systems are not linear, compensation is naturally decentralised, and the environment and user demands vary over time and seasonally [33]. Domestic loads, such as household appliances, can be divided according to the pattern of use into: (i) Devices operated according to the user's lifestyle or behaviour; (ii) Devices whose use is influenced by environmental variables, such as air temperature and humidity; and (iii) Devices operated depending on the state of the battery storing the energy produced, whether it exists [29].

A residential EMS plays a central role in meeting automated demand within a home, as most residential customers do not have the time or are proactive enough to execute recommended best practices manually. Such a system must manage loads with the least impact on the resident's lifestyle to be effective [34]. An example of applying an EMS follows: when residents sleep at night, the washing machine can start to work because the price of energy is low [35].

Different research address energy management through different methods and technologies. In [32], for example, they applied their algorithm to perform load measurement and forecast, grouping their profiles, measuring duration, and the probability of occurrence, thus generating the forecast for the next day. In [36], the authors take an approach based on a genetic algorithm to manage domestic loads' consumption. The consumption setpoint is determined according to the condition of distributed generation, resulting in a generation and energy tariff forecast. The ideal management aims to minimise load contingency considering consumer's preferences; that is, if consumption is less than the setpoint's limit, the system returns to the initial state; if consumption exceeds this setpoint, an optimisation process is necessary to determine which loads are to be withdrawn or reduced. In [33], the authors proposed an energy management solution that learns and adapts to residential energy use patterns. The adaptive neuro-fuzzy learning algorithm developed in this study makes the demand responses based on the following factors: peak load forecast, differential electricity prices, energy usage and budget patterns, social and environmental factors, and available solar energy.

III. INTELLIGENT ELECTRIC POWER MANAGEMENT SYSTEM (IEPMS) CONCEPT

The optimisation model aims to maximise a prosumer unit's energy savings according to its residents' consumption habits, influenced by local climatic conditions, for different pricing types. Figure 3 presents the intelligent system architecture for electric power management, considering information about energy generation and consumption simultaneously.

Figure 3 is structured in 3 main stages:

- **Optimisation problem variables** (detail (A) of Figure 3) – This class collects the variables that constitute the optimisation problem. The information includes the electrical loads of the consumer unit and the electrical equipment of the generating unit's PV system. These elements are strongly influenced by the heuristics and lifestyle of the prosumer unit residents, and the daily changes influence heuristics in climatic variables.
- **Energy demand** (detail (B) of Figure 3) – This class structures the information about consumer demand.

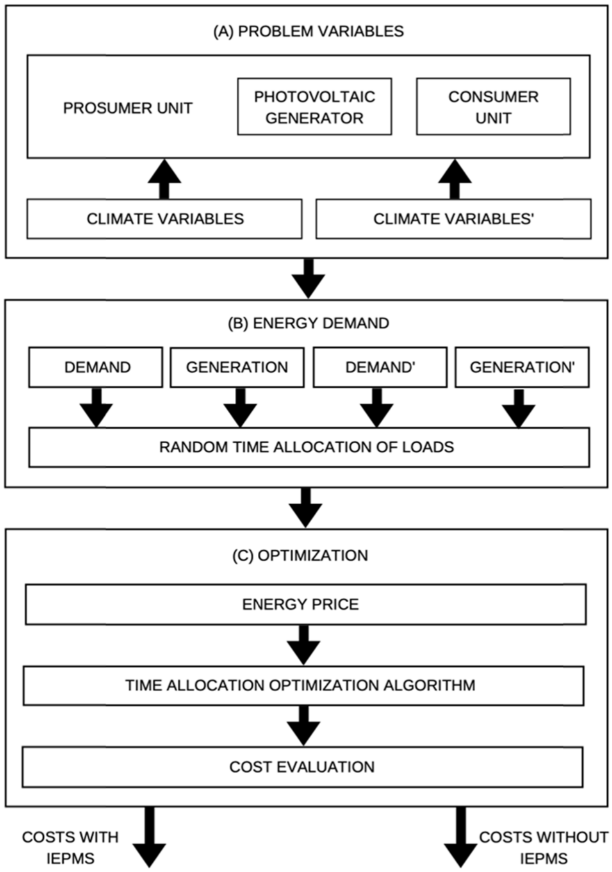

FIGURE 3. **Intelligent Electric Power Management System (IEPMS) architecture.**

The application of the composition methods for the next day's energy demand ($D + 1$) defines which loads will be set as on and will thus enter the load temporal allocation system. The daily power generation is also calculated. The loads are randomly allocated in time, respecting their restrictions according to the users' flexibility, heuristics, and habits. However, at this point, without any economic objective.

- **Optimisation Process** (detail (C) of Figure 3) – this class is responsible for carrying out the optimisation technique based on a genetic algorithm. The genetic algorithm receives the information from the previous groups and searches for the best Initial Operation Times (OPT_i) for each load, always aiming at the energy balance's best economic result. The different energy tariffs are considered individually. After the optimisation process, the costs for one year are evaluated.

A. VARIABLES OF THE OPTIMISATION PROBLEM

The optimisation problem variables are responsible for gathering the necessary information to input in the optimisation model. These variables were divided into three main subsets: (i) Prosumer Unit Data, (ii) Climate Conditions Data, and (iii) Pseudo-Climate Forecast Data. These subsets are detailed below.

1) PROSUMER UNIT DATA

The Prosumer Unit (PU) used as the experimental laboratory for this research is located in Porto União, Brazil and two people inhabit it. Consumption habits were observed, and a heuristic model was created to define the probability of filling loads. A stochastic model based on the heuristics model is the one that predicts which loads will be turned on the next day. The genetic algorithm is responsible to improve the load over time, always seeking to maximise the economy. The PU has the power generation unit (PV system) and the power consumption unit (consumer loads).

2) WEATHER DATA

This project used climate data conditions from the city of Curitiba, which is very similar to the city of Porto União. The data was provided by the Building energy efficiency laboratory (LabEEE) of the Federal University of Santa Catarina (UFSC) [37]. LabEEE has data available from 1969 to 2005, and it contains hourly averages for a set of climatic variables for each day of the year. The set of climatic variables available on this public dataset are dry bulb temperature (DBT) (°C), relative humidity (%), wind speed (m/s), and global horizontal radiation (GHR) (kWh/m^2). The option for this dataset of variables solves the impossibility of collecting local data in the necessary amount during the period foreseen for this research.

3) PSEUDO-CLIMATE FORECAST DATA

The model for forecasting climate variables for the next period ($D + 1$) is based on historical data. The parameter forecast hit percentage defines the forecast hit rate. If a hit rate of 100% is obtained for the solar radiation forecasting, the algorithm assumes historical data for the generation profile. For any other hit rate value, the model compares historical data of the day to historical data of the following days, selecting correct or wrong forecasting based on a comparative analysis of the solar radiation.

If a forecast is correct, it will be nearby the actual behaviour to be observed the next day. For a given data, referenced by the number of the day of the year (0 - 364), the algorithm initially establishes if the forecast will be correct or not, in the form of a Boolean variable.

The value of Root Mean Square Error (RMSE) calculated by the difference between two curves is used as the forecast quality metric, which one of these curves is the current day and the other taken from 45 days before and 45 days after the current date. In this case, for a correct forecast, the similarity between the forecast curve and the actual curve will be high, and the RMSE low. Note that the target day curve is known in advance because it uses the combined average historical data for several years. RMSE value ranges are used to define correct or wrong forecasts, to establish a tolerance for the similarity that characterises a correct forecast. Figure 4 presents an example of a correct forecast.

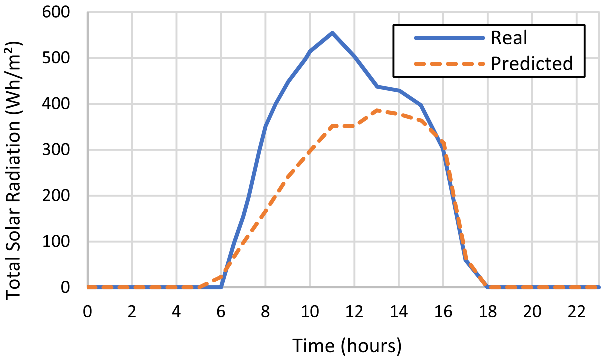

FIGURE 4. Example of what was considered a correct solar radiation forecast.

The limiting values of similarity adopted for the difference between the RMSE of the analysed curves that define the predictions as correct, for this research, are: (i) for temperature, less than or equal to 4°C; (ii) for humidity, less than or equal to 14%; (iii) for wind speed, less than or equal to 3 m/s; (iv) for solar radiation, less than or equal to 120 Wh/m^2. In this way, all values above those mentioned characterise wrong forecasts.

The algorithm selects, using one of the ranges according to the Boolean variable, all the curves with the calculated RMSE value (on the difference between the curves for each date and the next day) within the selected range. The average of all selected curves will be used as a forecast.

Ranges that define the desired level of similarity in the selection are defined by the user and adjusted for each variable. and directly influence the number of curves selected to form the average curve to be used as a forecast. One example of this strategy is when the hit rate is 95%, which means that at every 100 predictions, 5 will be inaccurate, reflecting in the forecasting. For comparison purposes, the methods will be evaluated for distinct hit rates.

This strategy for climate conditions forecasting introduces a stochastic component into the model due to the variability and uncertainties of the weather and how it influences the solar energy generation prediction and energy demand of the dwelling. Figure 5 presents the pseudo climate forecast flowchart.

B. ENERGY DEMAND

Routine data (Lifestyle) from the residential consumer unit inhabitants were collected concerning the habits of using electrical equipment to gather references to build the energy demand model. A load of the residential unit was identified to verify which of those can be managed. The residence is divided into eleven environments, totalling 68 electrical devices and total average power of 29.393 kW. Each load's individual power adopted as a parameter for the algorithm is the average value between the minimum and maximum operating power, respecting the inherent potency variations of loads having this characteristic, such as washing machine, flat iron, electric shower, and others.

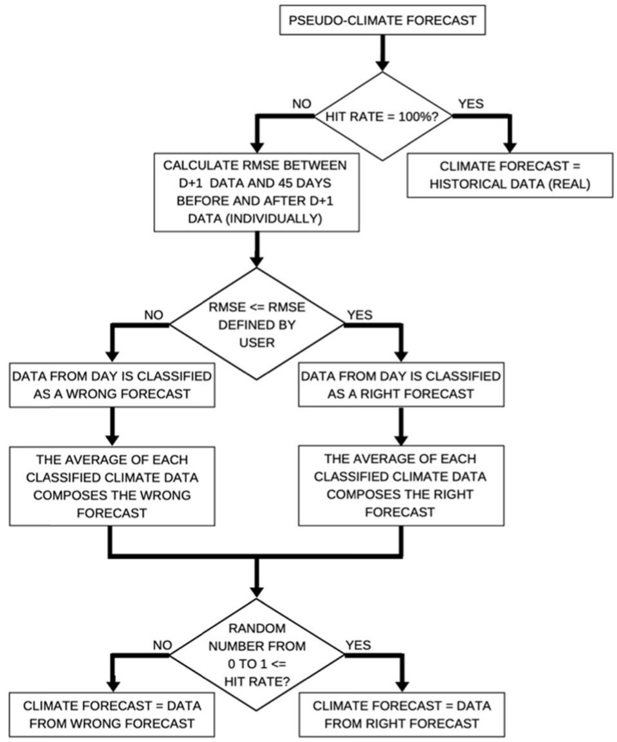

FIGURE 5. Pseudo climate forecast flowchart.

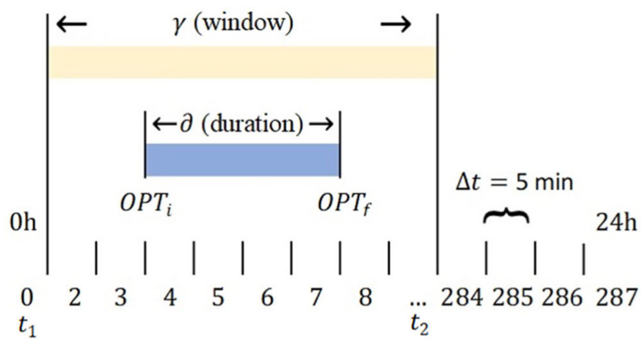

FIGURE 6. Operation window and load duration.

1) ENERGY DEMAND FORECAST

The demand for the following period ($D + 1$) is established in the form of a set of electrical loads. Each one is defined with the following parameters: (i) power P (W), (ii) electrical load duration ∂, (iii) start and end of a discretised period k (t_1 and t_2) when the operation can take place. The parameter γ in the model can take values between 0 and 287, as multiples of the 5-minute discretisation period, in 24 hours. Figure 6 shows a generic load within its operating period, where OPT_i represents the moment that the electrical load is switched on, and OPT_f is the moment that the electrical load is switched off.

The operation window is defined according to the residents' lifestyle and some parameters of the electrical loads that need the user's presence to be switched on, such as the hairdryer or the electric shower. Electrical loads that do not depend on the residents' presence to be switched on, such as the washing machine or swimming pool filter engine, have a larger operating window.

Equation (1) presents how the durations of loads operating are calculated. Equation (2) demonstrates how the load operating window is calculated. Flexibility equation is described in (3). Finally, equation (4) defines the duration of a load's operation and must always be lesser than or equal to its operating window.

$$\partial = OPT_f - OPT_i \tag{1}$$

$$\gamma = t_2 - t_1 \tag{2}$$

$$Flex = \frac{\gamma}{\partial} \tag{3}$$

$$\partial \leq \gamma \tag{4}$$

In equations (1)-(4), t_1 represents the starting time of the load's operation window (k), t_2 is the end time, ∂ is the duration of the load's operation (k), γ is the duration of the load's operation window (k), k represents periods of 5 minutes each, and $Flex$ is the flexibility of temporal allocation of a load.

When the flexibility is greater than 1, the user is more proactive to the algorithm's economic measures. A value close to 1 means that the user is more resistant to changes in their domestic routines, and consequently, it has less flexibility to allocate electrical loads in time.

For each electrical load, there is a stochastic model of occurrence according to its probability of occurrence function (POF), which can have a cumulative characteristic and is daily evaluated. The incidence (or not) of a load during $D+1$ is determined by evaluating its POF, which condenses all the influences contained in its heuristic. The heuristics capture all restrictions, preferences, dependencies, and recurrence defined by the residents. The load incidence, characterised by its parameters as described above, happens when there is an evaluation of the POF, along $(D+1)$, with a TRUE result.

The POF is constantly recalculated for the next day because the heuristic can include dependencies. The shape of the POFs in $(D + 1)$ results from the application of the heuristic, and it considers factors such as time since the last load occurred, climate conditions forecasts (temperature, humidity, wind speed, and solar radiation), dependent electrical loads, time since the occurrence of other loads, among other variables considered case by case, according to the characteristics of each load. For example, the heuristic may contain rules so that, preferably, clothes are not washed on rainy days but dry and windy days. On the other hand, the time elapsed since the last wash, which is associated with a progressive accumulation of dirty clothes, implies a greater probability that the function results in TRUE. However, the specific moment when an electrical load is activated will depend on the result of the optimisation process.

The resident's proactivity towards good economic practices is absorbed in the model by their acquiescence with a longer period in which the improvement system will be able to seek the best moment of execution associated with a load in the $D + 1$ period. For each load, this optimum moment will be informed to the resident, and, for this model, it will be assumed that it will have been observed. Proactivity is a feature built into the parameters chosen for each load. For example, a proactive energy-saving resident has a greater tolerance for accepting an indication of a bath time outside of the peak hours in the late afternoon; therefore, the operating window for this load is significantly longer than its duration. If the user is resistant to the suggested routine changes, the difference between the extension of the allocation interval and the operation duration will be slight.

The POF can be represented in Figure 7, an example in which the washing machine has a low probability of occurrence for day 1, gradually increasing each day until it reaches 100% on day 5. This example reflects a heuristic consumption habit, where the residents tend not to delay washing clothes for more than 5 days. In addition to the behaviour concerning time since the last operation, other variables can influence the POF value. If day 5 is a rainy day, the probability may drop to 90%, and the machine might not start despite the accumulation of dirty clothes. After this load, its probability of occurring on the following day is low again, as the user needs to accumulate dirty clothes until the subsequent use.

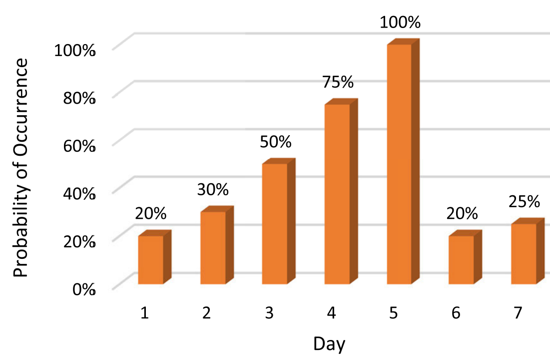

FIGURE 7. **Example of the POF of the washing machine.**

2) SCHEDULABLE EQUIPMENT

The electrical appliances subject to automated control (schedulable) were selected. These loads tend to have a larger operating window since they can be switched on without the user's presence. The schedulable loads and their operating windows are shown in Table 2, and they do not change in the face of profiles with distinct flexibility.

3) USER OPERATED EQUIPMENT

Appliances with higher consumption and a greater possibility of use reallocation were selected. These devices have different operating windows according to the flexibility of each user for each load. In the example of Table 3, it is possible

TABLE 2. Schedulable loads and their operating window.

Load	Days	Window 1	Daily window (hours)
Dishwasher	Mon to Sun	0:00 a.m. to 11:59 p.m.	24.00
Washing machine	Mon to Sun	0:00 a.m. to 11:59 p.m.	24.00
Clothes dryer	Mon to Sun	0:00 a.m. to 11:59 p.m.	24.00
Swimming pool engine	Mon to Sun	0:00 a.m. to 11:59 p.m.	24.00

TABLE 3. User operated equipment and their operating window.

Load	Day	Win* 1	Win 2	Win 3	Daily window (hours)
Electric shower	Mon to Fri	6:30 a.m. to 8:15 a.m.	12:00 p.m. to 1:15 p.m.	5:00 p.m. to 10:00 p.m.	8.00
	Sat	7:00 a.m. to 8:45 a.m.	12:00 p.m. to 10:00 p.m.		11.75
	Sun	9:00 a.m. to 10:00 p.m.			13.00
Treadmill	Mon to Fri	6:30 a.m. to 8:15 a.m.	12:00 p.m. to 1:15 p.m.	5:00 p.m. to 10:00 p.m.	8.00
	Sat	7:00 a.m. to 8:45 a.m.	12:00 p.m. to 10:00 p.m.		11.75
	Sun	9:00 a.m. to 10:00 p.m.			13.00
Vacuum cleaner	Mon to Fri	6:30 a.m. to 8:15 a.m.	12:00 p.m. to 1:15 p.m.	5:00 p.m. to 10:00 p.m.	8.00
	Sat	7:00 a.m. to 8:45 a.m.	12:00 p.m. to 10:00 p.m.		11.75
	Sun	9:00 a.m. to 10:00 p.m.			13.00
Pressure washer	Mon to Fri	5:00 p.m. to 7:00 p.m.			2.00
	Sat	12:00 p.m. to 7:00 p.m.			7.00
	Sun	9:00 a.m. to 7:00 p.m.			10.00
Hair straightener	Mon to Sun	6:30 a.m. to 8:15 a.m.	12:00 p.m. to 1:15 p.m.	10:00 p.m. to 11:00 p.m.	4.00
Hairdryer	Mon to Fri	6:30 a.m. to 8:15 a.m.	12:00 a.m. to 1:15 p.m.	5:00 p.m. to 10:00 p.m.	8.00
	Sat	7:00 a.m. to 8:45 a.m.	12:00 p.m. to 10:00 p.m.		11.75
	Sun	9:00 a.m. to 10:00 p.m.			13.00
Clothes iron	Mon to Fri	5:00 p.m. to 10:00 p.m.			5.00
	Sat	12:00 p.m. to 11:00 p.m.			11.00
	Sun	9:00 a.m. to 10:00 p.m.			13.00

to observe the loads and their operating windows for the user profile who works externally for a full shift of 8 hours daily.

4) ELECTRICAL LOAD PARAMETERS

The average operating time of each load was obtained through sampling during everyday use. Table 4 shows the parameters that will attend each electrical load for each day of the week. Furthermore, it will be used by the optimisation algorithm. In this example, the parameters are for the low flexibility profile, where the user works full time outside the dwelling.

5) ELECTRICAL LOAD HIERARCHY

Some household loads are dependents of other household activities, for example, habitually the iron will only be used after the washing. Another example observed is that immediately after using the treadmill, the electric shower will commonly be used. This load is hierarchically considered for the energy demand forecast and its activation moments, being part of the heuristics used in the energy efficiency optimisation model. Because of this, the hierarchy of load usage was defined and presented in Table 5.

6) IMPACT OF CLIMATE CONDITIONS

The routine of a home is affected by the local microclimate. Resident's habits are influenced by daily weather variations and will alter demand forecasts. The impacts of weather on the routine shown in Table 6 are built into the loads' heuristics and directly influence their POFs.

7) POWER GENERATION AND FORECAST

The prosumer unit uses climate-dependent power generation data. The climatic variables that were considered in this model that influence the energy generation are (i) DBT (°C) and (ii) GHR (kWh/m^2).

The installed power in photovoltaic modules is 1.53 kWp, and it must be corrected according to ambient temperature. This correction is possible using (5). The coefficient of power variation by temperature is found in the installed PV module's datasheet, defined as −0.0041 %/°C.

$$P_{PV} = P_{peak} + \left(P_{peak} * \left((DBT - 25) * CP_{temp}\right)\right) \quad (5)$$

where P_{PV} is the installed PV power corrected according to ambient temperature (W), P_{peak} is the photovoltaic power installed under the standard test conditions (W), and CP_{temp} is the temperature coefficient for maximum potency (%/°C).

The energy produced per hour is calculated as a function of installation data and the global horizontal radiation, as shown in (6) and (7). Efficiency data for both modules and inverter can be found in their datasheets, and in this case, the efficiencies are 17% and 97%, respectively. Other losses must be considered as wiring, connectors, partial shading, pollution,

TABLE 4. Electrical load parameters.

Days	Load	Power (W)	Duration (k)	Operation window (k) t_1	Operation window (k) t_2
Mon to Fri	Electric shower	5500	2	78	98
Mon to Fri			2	144	158
Mon to Fri			2	204	263
Saturday			2	84	104
Saturday			2	144	263
Sunday			2	108	263
Mon to Fri	Treadmill	1500	9	78	98
Mon to Fri			9	144	158
Mon to Fri			9	204	263
Saturday			9	84	104
Saturday			9	144	263
Sunday			9	108	263
Mon to Fri	Vacuum cleaner	1200	6	78	98
Mon to Fri			6	144	158
Mon to Fri			6	204	263
Saturday			6	84	104
Saturday			6	144	263
Sunday			6	108	263
Mon to Fri	Pressure washer	1800	12	204	227
Saturday			12	144	227
Sunday			12	108	227
Mon to Sun	Hair straightener	75	2	78	98
Mon to Sun			2	144	158
Mon to Sun			2	264	275
Mon to Fri	Hairdryer	1500	3	78	98
Mon to Fri			3	144	158
Mon to Fri			3	204	263
Saturday			3	84	104
Saturday			3	144	263
Sunday			3	108	263
Mon to Fri	Clothes iron	1000	28	204	263
Saturday			28	144	275
Sunday			28	108	263
Mon to Sun	Washing machine	1100	13	0	287
Mon to Sun	Dishwasher	1200	16	0	287
Mon to Sun	Swimming pool engine	368	12	0	287
Mon to Sun	Clothes dryer	1700	17	0	287

TABLE 5. Electrical load hierarchy.

Load holder	Dependent load
Treadmill	Electric shower
Electric shower	Hair dryer
Washing machine	Clothes iron
Washing machine	Clothes dryer

and so on, totalising 17%.

$$E_{hour} = GHR * A * Ef_{mod} * Ef_{inv} * (1 - Losses) \quad (6)$$

$$A = \frac{P_{pv}}{165} \quad (7)$$

where E_{hour} is the energy generated per hour (kWh), A is the area of the PV arrangement (m^2), Ef_{mod} is the average efficiency of a photovoltaic module (%), Ef_{inv} is the average efficiency of a photovoltaic inverter (%), and Losses are the system losses (connections, wiring, etc.) (%).

8) ENERGY PRICING

The system of this research considers an actual urban residential prosumer unit served at low voltage, and its pricing is defined following the concessionaire's commercial policies for this type of building, which is classified as subgroup B1 - residential. The energy consumed in the network is distributed by *Companhia Paranaense de Energia* (COPEL). There are two fares considered in this research: conventional fare and white fare

TABLE 6. Climate Conditions x Routine.

Climate	Routine	Consequence
High temperature	Take a bath	Increased probability
	Washing clothes	Increased probability
	Dry hair	Decreased probability
Low temperature	Running on the treadmill	Decreased probability
	Straighten hair	Decreased probability
	Dry clothes	Increased probability
	Take a bath	Decreased probability
	Filter pool	Decreased probability
High humidity	Washing clothes	Decreased probability
	Dry clothes	Increased probability
Low humidity	Washing clothes	Increased probability
High wind speed	Washing clothes	Increased probability
	Dry clothes	Decreased probability
High solar radiation	Dry hair	Decreased probability
	Washing clothes	Increased probability
	Filter pool	Increased probability
Low solar radiation	Washing clothes	Decreased probability

For the conventional fare, the homologation resolution No. 2.259, of June 18, 2019, establishes energy tariffs (TE) and Tariffs for the Use of the Distribution System (TUSD) referring to *COPEL Distribuição S.A.* (COPEL-DIS) [38]. The tariffs assumed in this study are 0.517 R$/kWh and 0.798 R$/kWh, including taxes.

From January 2018, energy consumers can adhere to tariff rules according to the time of use. This modality is called the white energy tariff. The consumption schedule is classified as (i) peak hours, when many consumers are using energy at the same time, overloading the electrical system; (ii) intermediate hours, representing one hour before and one hour after the peak hours; (iii) off-peak hours, which does not coincide to the previously mentioned periods.

When the consumer concentrates his consumption in the off-peak period, it is possible to reduce the expenses with electric energy and, at the same time, relieve the energy distribution system, reducing the need for investments to improve the grid. Paraná state electricity distributor, the COPEL company, defined its schedule for the white tariff according to Table 7.

TABLE 7. Definition of COPEL's consumption schedules.

Tariff post	Schedule
Peak	6:00 p.m. to 9:00 p.m.
Intermediate	5:00 p.m. to 6:00 p.m. and 9:00 p.m. to 10:00 p.m.
Off-peak	10:00 p.m. to 5:00 p.m.

The white tariff is the best option for consumers who may have a large part of their consumption concentrated during off-peak periods. Additionally, on weekends and official national holidays, all hours of the day are considered off-peak. The base amount applied in the billing calculation is the conventional tariff, this changing depending on the time of use. Figure 8 summarises the concessionaire's hourly charging model.

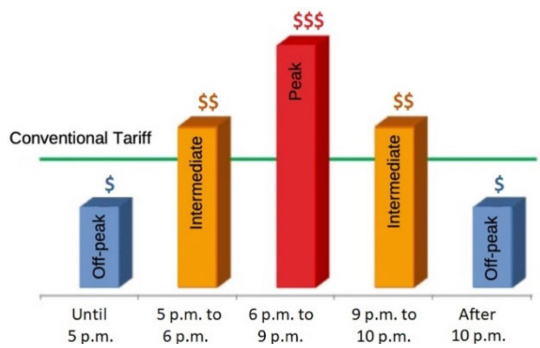

FIGURE 8. White energy tariff schedules and values (adapted from [39]).

Table 8 shows COPEL's white tariff costs, which will be applied in this research [39]. The percentages presented for each schedule are approximate; the current data should be consulted directly at the energy company.

TABLE 8. Conventional and white tariff.

Type of energy tariff	Percentage of conventional tariff	Cost (R$/kWh)
Conventional tariff with taxes	100%	R$ 0.798
White tariff - off-peak	85%	R$ 0.685
White tariff - intermediate	117%	R$ 0.936
White tariff - peak	182%	R$ 1.454

C. OPTIMIZATION ALGORITHM

The optimisation algorithm employs the set of enabled electrical loads combined with the generation forecast to predict the best activation moments throughout the period $(D+1)$, that is, maximising energy savings, considering its possible commercialisation [40].

Given the demand scenario and its flexibility to allocate loads for the next day, the optimisation algorithm assumes the vector initial operation times (OPT_i) of the electrical loads set to TRUE, thus defining their activation moments, seeking the lowest daily energy cost. OPT_i It can be within the operating window for each day, respecting each load's duration, dependencies, and other rules. Equation (8) demonstrates this condition.

$$t_2 - \partial > OPTi_i > t_1 \tag{8}$$

1) OBJECTIVE FUNCTION

The objective function reflects the search for the maximum economic efficiency of the prosumer unit. The problem's objective function can be represented by calculating the daily cost of energy, which is the sum of the energy balance cost for each k period analysed during the 24 hours of the day. If the cost of traded energy is positive, the user is consuming and paying for the company's energy. If it is negative, the user is selling the excess of energy produced to the concessionaire, generating credits for subsequent consumption. The problem formulation of this research can be seen in (9).

$$min\$Day = \sum_{k=0}^{287} \$E_{com_k} \tag{9}$$

where $\$Day$ is the daily energy cost (R\$); $\$E_{com_k}$ is the cost of energy sold in period k (R\$). Equation (10) demonstrates how $\$E_{com_k}$ is calculated. If the marketed power is positive, purchase pricing is used. If it is negative, the sale tariff is used.

$$\$E_{com_k} = P_{com_k} * \Delta t * \$TE \tag{10}$$

where P_{com_k} is the power traded in period k (kW), and $\$TE$ is the cost of the instant energy fare (R\$).

The energy balance of the residence in period k is considered through the difference between instantaneous and generated power to calculate the power commercialised. Equation (11) presents the energy balance. If the marketed potency is positive, it means that the user is currently consuming energy from the concessionaire. If it is negative, the user is injecting energy into the concessionaire's grid.

$$P_{com_k} = P_{inst_k} - P_{ger_k} \tag{11}$$

In (11), P_{inst_k} is the total instantaneous potency in period k (kW), and P_{ger_k} represents the potency generated in the period k (kW). Finally, the calculation of the total instantaneous potency is performed through (12), where all the individual potencies of each load in period k are added. The loads used in the equation range from 1 to n, varying according to the selection of which will be switched on for period $D + 1$.

$$P_{inst_k} = \sum_{i=1}^{n} P_{i,k} \tag{12}$$

where $P_{i,k}$ is the instantaneous potency of load i in period k (kW).

IV. INTELLIGENT ELECTRIC POWER MANAGEMENT SYSTEM EXPERIMENTAL APPLICATION

The IEPMS was validated in 26 different scenarios to compare the optimisation algorithm's model efficiency and performance.

A. APPLICATION SCENARIOS

The application scenarios were divided according to 4 groups of usage patterns (i) ideal theoretical (ii) home office, (iii) part-time external work, and (iv) full-time external work. Each group has several individuals that are differentiated by the following characteristics: (a) flexibility, (b) energy fare, (c) climate forecast hit rate.

Flexibility indicates how flexible the user is in allocating loads in time. The ideal theoretical usage pattern is one where all electrical loads can be allocated at any time interval on the day $(D + 1)$, that is, in any period k between 0 and 287. The most restricted usage pattern is when the user has few allocation windows for the electrical loads. In the proposed model, it is represented by the full-time external work, where the user stays less time at home, being less available to activate electrical loads.

The energy fare is the conventional category, which is the standard category used for this prosumer unit, and the white tariff, which has different pricing according to the time of day. The hit rate of the climate forecast indicates the forecast percentage for the next day $(D + 1)$ that will be correct. The ideal theoretical usage pattern uses previously known climatic data, and consequently, it represents a 100% hit rate. The scenarios will be tested with other individuals having hit rates ranging between 95%, 90%, and 85% to compare performance. Table 9 shows all application scenarios and their identification (IDs).

1) IDEAL THEORETICAL

In these scenarios, two individuals differ in the tariff plan. As mentioned earlier, these individuals have maximum flexibility for allocating loads in time. The weather forecast hit of 100% ensures that the loads are predicted and set as TRUE with perfect precision for the following day $(D + 1)$. These characteristics allow the algorithm to seek its maximum theoretical economy for both the conventional and the white tariff.

2) HOME OFFICE

For the remote work scenarios or home office, we consider that the flexibility is higher because the residents working at home can allocate their electrical equipment in wider windows.

3) PART-TIME EXTERNAL WORK

Here the residents work part-time outside and part-time at home. Thus, we can say that they have average flexibility to allocate loads in time. In this example, when they are away, some loads that depend on the resident cannot be switched on, thus reducing their operation.

4) PART-TIME EXTERNAL WORK

Finally, in the part-time external work, the residents work 8 hours outside the home, which reduces the size of the load operation windows, allowing the operation of some loads in the morning, before business hours, during lunch breaks, and after 6 p.m. For this reason, flexibility is low.

TABLE 9. Application scenarios.

ID	Usage Pattern	Flexibility	Energy tariff	Forecast hit
01	Ideal theoretical	Maximum	Conventional	100%
02	Ideal theoretical	Maximum	White	100%
03	Home office	High	Conventional	100%
04	Home office	High	White	100%
05	Home office	High	Conventional	95%
06	Home office	High	White	95%
07	Home office	High	Conventional	90%
08	Home office	High	White	90%
09	Home office	High	Conventional	85%
10	Home office	High	White	85%
11	Part-time external work	Medium	Conventional	100%
12	Part-time external work	Medium	White	100%
13	Part-time external work	Medium	Conventional	95%
14	Part-time external work	Medium	White	95%
15	Part-time external work	Medium	Conventional	90%
16	Part-time external work	Medium	White	90%
17	Part-time external work	Medium	Conventional	85%
18	Part-time external work	Medium	White	85%
19	Full-time external work	Low	Conventional	100%
20	Full-time external work	Low	White	100%
21	Full-time external work	Low	Conventional	95%
22	Full-time external work	Low	White	95%
23	Full-time external work	Low	Conventional	90%
24	Full-time external work	Low	White	90%
25	Full-time external work	Low	Conventional	85%
26	Full-time external work	Low	White	85%

B. COMPOSITION OF DELAY PROBABILITY OF OCCURRENCE FUNCTION

The rules that make up the daily Probability of Occurrence Function (POF) for each load are called heuristics. They were modelled according to the consumption habits of the residents of the analysed prosumer unit. Table 10 shows how each load behaves according to its heuristics for day 4 in the ideal theoretical scenario. The POFs define the probability of occurrence for the day evaluated. These rules are applied individually and daily for each load and are responsible for increasing or decreasing the probability that the load will be part of the daily energy demand.

The algorithm stochastically chooses a value between 0 and 1 for each load daily. When the value is less than the value of the POF, the load is set to be switched on for this day, thus composing the daily demand.

TABLE 10. Loads and their *POF*s for the evaluated day.

Equipment	Day	*POF*	Stochastic value	On/Off
Electric shower 1	4	1.9500	0.723939139	On
Electric shower 2	4	1.9500	0.475088611	On
Electric shower 3	4	0.1345	0.596663775	Off
Electric shower 4	4	0.1852	0.066969424	On
Electric shower 5	4	0	0.072562138	Off
Treadmill 1	4	0.6000	0.198976026	On
Treadmill 2	4	0.3000	0.151860997	On
Clothes iron	4	0.4800	0.100104345	On
Washing machine	4	0.2092	0.129293865	On
Hair dryer 1	4	0.0243	0.553277732	Off
Hair dryer 2	4	0.0324	0.187814825	Off
Hair dryer 3	4	0	0.952101243	Off
Clothes dryer	4	0.0724	0.681611779	Off
Swimming pool engine	4	0.8680	0.541019673	On
Hair straightener	4	0.1568	0.707180601	Off
Dishwasher	4	0.3500	0.263886671	On
Vacuum cleaner	4	0.3200	0.926725684	Off
Pressure washer	4	0.0800	0.839193058	Off

C. ENERGY DEMAND FOR THE PROPOSED SCENARIOS

For each hit rate of the climate forecast, there is an influence on the POF and a different demand composition. In Table 11, we can see how different hit rates of climate forecast influence the number of incidences of each load for 1 year. Some loads do not influence the use due to climate variation, and as a result, their incidence does not change with the different rates of correct predictions.

D. PARAMETERS OF THE GENETIC ALGORITHM

Considering the complexity of the optimisation problem, optimal operation of photovoltaic units subjected to specific electrical loads, combined with the generation forecast and the prediction of the best activation moments to maximise energy savings, can be stated as a mixed-integer nonlinear programming (MINLP) problem [10]. To avoid simplifications in the problem formulation, the Genetic Algorithm was adopted to prevent exploring the entire search space associated with the decision variables mentioned above. Moreover, this well-established metaheuristic technique has shown significant results in recent applications involving the design [41], [42] and the optimisation strategy [43] of photovoltaic systems.

Different configuration parameters of the genetic operators were tested to obtain a better result. The crossover is done at only one point, the chromosome, respecting the rule of

TABLE 11. Incidence of loads for different climatic forecasts.

Electrical Loads	Incidence of different rates			
	100%	95%	90%	85%
Electric shower 1	348	350	350	350
Electric shower 2	357	356	356	355
Electric shower 3	16	15	15	15
Electric shower 4	18	18	18	17
Electric shower 5	13	13	13	13
Treadmill 1	136	138	139	139
Treadmill 2	115	118	117	116
Clothes iron	49	51	51	52
Washing machine	75	75	76	76
Hair dryer 1	42	40	40	39
Hair dryer 2	78	71	69	70
Hair dryer3	13	13	13	13
Clothes dryer	24	33	35	38
Swimming pool engine	110	101	102	99
Hair straightener	65	54	53	52
Dishwasher	202	202	202	202
Vacuum cleaner	88	88	88	88
Pressure washer	30	33	34	34

charges dependence, which does not separate these genes during the crossover between parents. The definition of other adopted parameters occurred after applying the algorithm to a sample of 10% of the days (36 days). The three mutation rates that achieved the lowest cost from the initial assessment were selected and tested again for different initial populations and different numbers of generations for the same sample. Mutation rates of 0.25, 0.1, and 0.3 were selected and tested for the initial populations of 5 and 10 individuals, evolving for 100 and 200 generations. The difference between the two lowest costs found for the 36 days is only R$ 0.285, or 0.398%.

Also, the time necessary to improve the 365 days was evaluated for the initial populations and numbers of intended generations at this stage. It is required 15.51 hours to enhance the 365 days of the year, evolving 100 generations, with an initial population of 5 individuals. Evolving to 200 generations with an initial population of 10 individuals required 50.25 hours. Thus, using the fastest method, with less computational cost, there is a gain of 69% in the optimisation speed and a loss of only 0.398% in the other parameter's cost value.

Given the previously mentioned information, the algorithm was parameterised with an initial population of 5 individuals and 100 generations, thus achieving agility in the optimisation process for each scenario during t year, with a relatively low computational cost. The rate mutation adopted is 0.25, which during initial sampling presented the best result for these parameters.

E. RESULTS WITH THE APPLICATION OF IEPMS

The results for the period of one year, referenced to the year 2019, were computed for each proposed scenario. The cost without IEPMS represents the sum of the 365 worst daily results among the algorithm's initial population before the optimisation process. The cost with IEPMS represents the sum of the 365 best daily results among all individuals generated after the optimisation process. In all scenarios, the algorithm was able to provide savings for the residential prosumer unit.

It is important to emphasise that the present study was applied to an actual prosumer unit, and the energy consumption is based on the occupants' routine using the available loads. The idea is to affect occupants' lifestyle as little as possible, saving energy wherever the system identifies the possibility of carrying out this task. The system performance was measured through different hit rates, those associated with climate forecasting. Finally, the comparison regarding energy consumption without and with the proposed method indicates the benefits of the proposed strategy.

Figure 9 demonstrates how the algorithm sees demand and generation power before the optimisation process. Figure 10 shows how the algorithm reallocates the same demand presented above, shifting the OPT_i of each load, providing the best financial result for the day after the optimisation process.

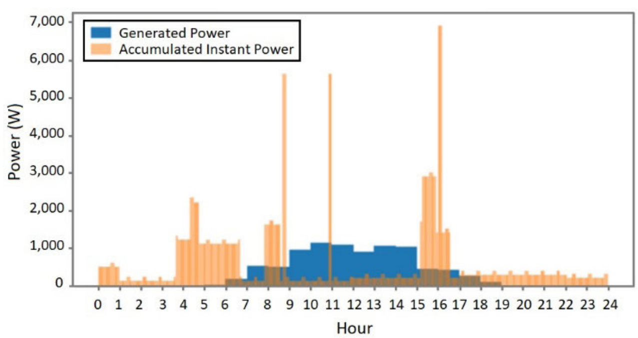

FIGURE 9. Demand before optimisation.

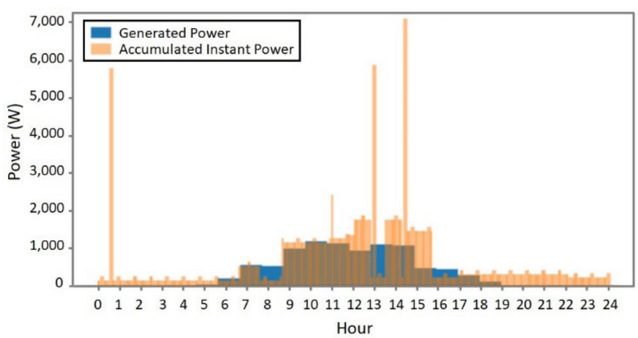

FIGURE 10. Demand after optimisation.

Table 12 depicts the electricity costs for one year without and with the use of IEPMS. The annual cost for the ideal theoretical scenario using the conventional tariff with IEPMS was R$ 1,114.07. The annual cost for the same scenario, using the white rate, was R$ 1,151.22.

TABLE 12. Costs obtained for the theoretical scenarios.

Scenario	Costs without IEPMS	Costs with IEPMS	Economy %
01	R$ 1,175.97	R$ 1,114.07	5.26
02	R$ 1,562.04	R$ 1,151.22	26.30

Table 13 shows the electricity costs for one year without and using IEPMS for the home office scenarios.

TABLE 13. Costs obtained for the home office scenarios.

Scenario	Costs without IEPMS	Costs with IEPMS	Economy %
03	R$ 1,171.39	R$ 1,112.63	5.02
04	R$ 1,636.40	R$ 1,149.70	29.74
05	R$ 1,193.18	R$ 1,135.60	4.83
06	R$ 1,672.55	R$ 1,168.65	30.13
07	R$ 1,192.26	R$ 1,134.71	4.83
08	R$ 1,662.81	R$ 1,167.74	29.77
09	R$ 1,195.22	R$ 1,137.90	4.80
10	R$ 1,666.69	R$ 1,170.32	29.78

In the sequence, Table 14 shows the electricity costs for one year without and with the use of IEPMS for the part-time external work scenarios, and Table 15 presents the electricity costs for one year without and with the use of IEPMS for the full-time external work scenarios.

TABLE 14. Costs obtained for the part-time scenarios.

Scenario	Costs without IEPMS	Costs with IEPMS	Economy %
11	R$ 1,173.64	R$ 1,115.38	4.96
12	R$ 1,696.92	R$ 1,152.04	32.11
13	R$ 1,195.41	R$ 1,137.80	4.82
14	R$ 1,727.14	R$ 1,170.70	32.22
15	R$ 1,194.25	R$ 1,136.84	4.81
16	R$ 1,728.41	R$ 1,169.84	32.32
17	R$ 1,197.39	R$ 1,140.00	4.79
18	R$ 1,732.86	R$ 1,172.34	32.35

V. DISCUSSION

Different user profiles, distinct energy tariffs, and different climate forecast accuracy rates were applied in 26 scenarios.

TABLE 15. Costs obtained for the full-time scenarios.

Scenario	Costs without IEPMS	Costs with IEPMS	Economy %
19	R$ 1,176.93	R$ 1,124.56	4.45
20	R$ 1,853.54	R$ 1,209.96	34.72
21	R$ 1,198.61	R$ 1,147.73	4.24
22	R$ 1,885.06	R$ 1,232.80	34.60
23	R$ 1,197.74	R$ 1,146.78	4.25
24	R$ 1,886.69	R$ 1,231.74	34.71
25	R$ 1,201.08	R$ 1,150.03	4.25
26	R$ 1,890.59	R$ 1,234.75	34.69

TABLE 16. Results for the white tariff scenarios.

Scenario	Costs without IEPMS	Costs with IEPMS	Economy %
20	R$ 1,853.54	R$ 1,209.96	34.72
24	R$ 1,886.69	R$ 1,231.74	34.71
26	R$ 1,890.59	R$ 1,234.75	34.69
22	R$ 1,885.06	R$ 1,232.80	34.60
18	R$ 1,732.86	R$ 1,172.34	32.35
16	R$ 1,728.41	R$ 1,169.84	32.32
14	R$ 1,727.14	R$ 1,170.70	32.22
12	R$ 1,696.92	R$ 1,152.04	32.11
06	R$ 1,672.55	R$ 1,168.65	30.13
10	R$ 1,666.69	R$ 1,170.32	29.78
08	R$ 1,662.81	R$ 1,167.74	29.77
04	R$ 1,636.40	R$ 1,149.70	29.74
02	R$ 1,562.04	R$ 1,151.22	26.30

Tables 16 to 17 show the results of the optimisation algorithm in all scenarios considered in this study. A discussion regarding the economic efficiency and performance of IEPMS was carried out and is presented in the sequence.

The efficiency of IEPMS was measured by comparing the savings provided in the period analysed for the different scenarios proposed after applying IEPMS, with the same scenarios without applying IEPMS. Savings were shown to be more significant for scenarios that used the white electricity tariff, where flexibility is more restricted than in the full-time external work profile. For this standard, the allocation options in the intervals where the energy is low-cost are less, and the regular use of electrical equipment is made in the periods when the energy is more expensive (intermediate and peak hours), making the daily cost bigger.

The maximum savings for this tariff was 34.72% for ID-20, going from an annual cost of R$ 1,853.54 to R$ 1,209.96. The lowest savings provided were for

TABLE 17. Results obtained for the conventional tariff scenarios.

Scenario	Costs without IEPMS	Costs without IEPMS	Economy %
01	R$ 1,175.97	R$ 1,114.07	5.26
03	R$ 1,171.39	R$ 1,112.63	5.02
05	R$ 1,193.18	R$ 1,135.60	4.83
07	R$ 1,192.26	R$ 1,134.71	4.83
09	R$ 1,195.22	R$ 1,137.90	4.80
11	R$ 1,173.64	R$ 1,115.38	4.96
13	R$ 1,195.41	R$ 1,137.80	4.82
15	R$ 1,194.25	R$ 1,136.84	4.81
17	R$ 1,197.39	R$ 1,140.00	4.79
19	R$ 1,176.93	R$ 1,124.56	4.45
21	R$ 1,198.61	R$ 1,147.73	4.24
23	R$ 1,197.74	R$ 1,146.78	4.25
25	R$ 1,201.08	R$ 1,150.03	4.25

ID-02 with 26.30%, reducing the annual cost of R$ 1,562.04 to R$ 1,151.22. Table 16 presents scenarios that showed the most significant savings when applying the white tariff in decreasing order.

For conventional tariff scenarios, the annual savings were lower. In applying this tariff, the algorithm proved to be more effective for scenarios with greater flexibility for allocating loads in time, that is, the most significant savings occurred in the ideal theoretical usage pattern. Moreover, the annual cost values without and with the IEPMS are similar because the variation in energy cost is smaller and occurs only in the concessionaire's portion. This tariff's maximum savings was 5.26% for ID-01, reducing an annual cost of R$ 1,175.97 to R$ 1,114.07. The lowest savings provided was for ID-25 with 4.25%, coming from an annual cost of R$ 1,201.08 to R$ 1,150.03. Table 17 shows the scenarios that presented the greatest savings when applying the conventional tariff, in decreasing order.

Each proposed scenario has its specificity, and therefore, the initial populations and their descendant generations will have variations. Theoretically, the lowest cost for both conventional and white tariffs should be in scenarios with the greatest flexibility in allocating loads in time. What was demonstrated in the study is that the home office scenarios achieved a slightly lower annual cost than the ideal theoretical scenarios. The home office scenarios have high flexibility, close to the theoretical scenarios, but as the restrictions, in this case, were positive for the model, they helped the algorithm to allocate loads at better (more economical) times. The home office scenario restrictions made it possible for an initial population to be generated with higher quality, enabling evolution and improvement with an even better annual cost. Table 18 lists the scenarios in ascending order of the total cost of electric energy achieved after the IEPMS optimisation in the analysed period.

TABLE 18. Scenarios in ascending order regarding the total cost of electric energy after optimisation.

Scenario	Costs with IEPMS	Costs without IEPMS	Economy %
03	R$ 1,171.39	R$ 1,112.63	5.02
01	R$ 1,175.97	R$ 1,114.07	5.26
11	R$ 1,173.64	R$ 1,115.38	4.96
19	R$ 1,176.93	R$ 1,124.56	4.45
07	R$ 1,192.26	R$ 1,134.71	4.83
05	R$ 1,193.18	R$ 1,135.60	4.83
15	R$ 1,194.25	R$ 1,136.84	4.81
13	R$ 1,195.41	R$ 1,137.80	4.82
09	R$ 1,195.22	R$ 1,137.90	4.80
17	R$ 1,197.39	R$ 1,140.00	4.79
23	R$ 1,197.74	R$ 1,146.78	4.25
21	R$ 1,198.61	R$ 1,147.73	4.24
04	R$ 1,636.40	R$ 1,149.70	29.74
25	R$ 1,201.08	R$ 1,150.03	4.25
02	R$ 1,562.04	R$ 1,151.22	26.30
12	R$ 1,696.92	R$ 1,152.04	32.11
08	R$ 1,662.81	R$ 1,167.74	29.77
06	R$ 1,672.55	R$ 1,168.65	30.13
16	R$ 1,728.41	R$ 1,169.84	32.32
10	R$ 1,666.69	R$ 1,170.32	29.78
14	R$ 1,727.14	R$ 1,170.70	32.22
18	R$ 1,732.86	R$ 1,172.34	32.35
20	R$ 1,853.54	R$ 1,209.96	34.72
24	R$ 1,886.69	R$ 1,231.74	34.71
22	R$ 1,885.06	R$ 1,232.80	34.60
26	R$ 1,890.59	R$ 1,234.75	34.69

The model's performance was measured according to the absolute and relative errors for each hit rate of climate forecast, related to the annual costs achieved with the use of IEPMS in the ideal theoretical scenarios, for the comparative scenarios. As a result of the model's application, we can observe that, in all scenarios, the performance was not less than 97% for hit rates of climate forecast that varied between 95, 90, and 85%. For the study in question, an error value of up to 15% in the forecast of climatic variables did not represent significant losses in the financial result.

A wrong forecast does not necessarily mean an increase in electricity costs but may even cause the opposite effect. If the inadequate forecast is a sunny day, it will have a high energy production and, consequently, a lower energy balance cost. The energy generating system depends exclusively on the climate, and the potency generated is significantly affected by climatic variables. The electric loads depend on climate conditions. However, they also depend on the heuristics that compose their *POF*s, thus suffering less influence under a wrong climate forecast. The demand for daily consumption did not change significantly because of different climatic forecasts.

VI. CONCLUSION AND RECOMMENDATIONS

With the creation of an intelligent system for managing electricity, it was possible to apply and measure its efficiency in an energy prosumer unit aiming for maximum economic efficiency. This article explored the concepts of energy prosumer and how it relates to energy management systems.

The architecture of an intelligent energy management system was created, and the authors define how it can provide energy savings while minimising the impact on the lifestyle of residents of a prosumer unit. With the system architecture defined, the computational development and implementation of an algorithm were started to maximise the energy prosumer unit's economy, considering the incidence of demand on a stochastic basis, according to the residents' habits.

Through the application of the algorithm, it was possible to evaluate the performance of the system concerning the ideal theoretical scenario and the proposed scenarios of the home office, part-time external work and full-time external work, considering conventional and white tariffs, and different accuracy rates for forecasting climatic variables over a year. Finally, the results achieved in a prosumer unit's economic performance endowed with IEPMS were discussed compared to the reference scenario, that is, without IEPMS.

In this research, the IEPMS proved effective for the energy prosumer unit's economic maximisation, demonstrating an intelligent alternative of electricity management on the demand side in a residential prosumer unit in Brazil. This research used climatic data from the LabEEE for the city of Curitiba. These data were used because there was not enough time to collect reliable data and the amount needed for this project. The data may be replaced in the future by data from a local weather station, reflecting updated information from the local microclimate.

The residence chosen as a laboratory for this research has several electrical loads that operate for a short time or in cycles, and others remain on standby for long periods, such as television, microwave oven, wi-fi router, refrigerator, among others. The model considered an average value of potency and operation duration for these cases, calling this demand base electrical loads. The base loads have slight variations between them due to the day of the week and time, making up a baseline demand for the day $(D+1)$. Although the base loads represent a relevant consumption at the end of the day, they cannot be reallocated by the optimisation algorithm.

For future research, smart energy meters capable of reporting more accurately and in real-time can implement baseline demand variation. The costs of energy pricing adopted in this work were close to reality, considering that the energy sold to the concessionaire is worth, on average, 15% less than the energy purchased. This difference is due to the collection of taxes on TUSD in the energy injected into the distribution grid. This portion of the tariff is not covered by the tax exemption agreement established by the federal government. The savings related to tariff fare, which are seasonally included in tariffs due to variations in energy availability and demand in the national energy matrix and according to each unit consumption, are not considered in this model. Another suggestion for future work is the application of other optimisation methods, comparing efficiency against the model and methods proposed here.

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REFERENCES

[1] G. Dileep, "A survey on smart grid technologies and applications," *Renew. Energy*, vol. 146, pp. 2589–2625, Feb. 2020, doi: 10.1016/j.renene.2019.08.092.

[2] M. Schappert and M. von Hauff, "Sustainable consumption in the smart grid: From key points to eco-routine," *J. Cleaner Prod.*, vol. 267, Sep. 2020, Art. no. 121585, doi: 10.1016/j.jclepro.2020.121585.

[3] O. Majeed Butt, M. Zulqarnain, and T. Majeed Butt, "Recent advancement in smart grid technology: Future prospects in the electrical power network," *Ain Shams Eng. J.*, vol. 12, no. 1, pp. 687–695, Mar. 2021, doi: 10.1016/j.asej.2020.05.004.

[4] M. Yaqoot, P. Diwan, and T. C. Kandpal, "Review of barriers to the dissemination of decentralized renewable energy systems," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 477–490, May 2016, doi: 10.1016/j.rser.2015.12.224.

[5] *Resolução Normativa No 678, de 1o de Setembro de 2015*, (in Portuguese), Nat. Energy Agency Brazil (ANEEL), Brasilia, Brazil, 2015. [Online]. Available: https://www.in.gov.br/materia/-/asset_publisher/Kujrw0TZC2Mb/content/id/32853619/do1-2015-09-16-resolucao-normativa-n-678-de-1-de-setembro-de-2015-32853615

[6] ANEEL. (2017). *Nota Técnica n° 0056/2017-SRD/ANEEL.* (in Portuguese). Online]. Available: https://www.aneel.gov.br/documents/656827/15234696/Nota+Técnica_0056_PROJEÇÕES+GD+2017/

[7] S. D. Ramchurn, P. Vytelingum, A. Rogers, and E. N. R. Jennings, "Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence," *Commun. ACM*, vol. 55, no. 4, pp. 86–97, 2012, doi: 10.1145/2133806.2133825.

[8] M. K. Behera, I. Majumder, and N. Nayak, "Solar photovoltaic power forecasting using optimized modified extreme learning machine technique," *Eng. Sci. Technol., Int. J.*, vol. 21, no. 3, pp. 428–438, Jun. 2018, doi: 10.1016/j.jestch.2018.04.013.

[9] A. Dimovski, M. Moncecchi, D. Falabretti, and M. Merlo, "PV forecast for the optimal operation of the medium voltage distribution network: A real-life implementation on a large scale pilot," *Energies*, vol. 13, no. 20, p. 5330, Oct. 2020, doi: 10.3390/en13205330.

[10] C. Sabillon, J. F. Franco, M. J. Rider, and R. Romero, "Joint optimal operation of photovoltaic units and electric vehicles in residential networks with storage systems: A dynamic scheduling method," *Int. J. Electr. Power Energy Syst.*, vol. 103, pp. 136–145, Dec. 2018, doi: 10.1016/j.ijepes.2018.05.015.

[11] S. Ahmad, A. Ahmad, M. Naeem, W. Ejaz, and H. Kim, "A compendium of performance metrics, pricing schemes, optimization objectives, and solution methodologies of demand side management for the smart grid," *Energies*, vol. 11, no. 10, p. 2801, Oct. 2018, doi: 10.3390/en11102801.

[12] R. Suzuki, Y. Hayashi, and E. Y. Fujimoto, "Determination method of optimal planning and operation for residential PV system and storage battery based on weather forecast," in *Proc. IEEE Int. Conf. Power Energy (PECon)*, Dec. 2012, pp. 343–347, doi: 10.1109/PECon.2012.6450235.
[13] X. Wang, A. Palazoglu, and E. N. H. El-Farra, "Operation of residential hybrid renewable energy systems: Integrating forecasting, optimization and demand response," in *Proc. Amer. Control Conf.*, Jun. 2014, pp. 5043–5048, doi: 10.1109/ACC.2014.6859105.
[14] R. Yaqub, S. Ahmad, A. Ahmad, and M. Amin, "Smart energy-consumption management system considering consumers' spending goals (SEMS-CCSG): SEMS-CCSG," *Int. Trans. Electr. Energy Syst.*, vol. 26, no. 7, pp. 1570–1584, Jul. 2016, doi: 10.1002/etep.2167.
[15] L. Wang, Q. Li, R. Ding, M. Sun, and G. Wang, "Integrated scheduling of energy supply and demand in microgrids under uncertainty: A robust multi-objective optimization approach," *Energy*, vol. 130, pp. 1–14, Jul. 2017, doi: 10.1016/j.energy.2017.04.115.
[16] V. Palakonda, N. H. Awad, R. Mallipeddi, M. Z. Ali, K. C. Veluvolu, and E. P. N. Suganthan, "Differential evolution with stochastic selection for uncertain environments: A smart grid application," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2018, pp. 1–7, doi: 10.1109/CEC.2018.8477809.
[17] D. Neves, A. Pina, and C. A. Silva, "Comparison of different demand response optimization goals on an isolated microgrid," *Sustain. Energy Technol. Assessments*, vol. 30, pp. 209–215, Dec. 2018, doi: 10.1016/j.seta.2018.10.006.
[18] S. Ahmad, M. Naeem, and A. Ahmad, "Unified optimization model for energy management in sustainable smart power systems," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 4, pp. 1–18, Apr. 2020, doi: 10.1002/2050-7038.12144.
[19] M. Yang, J. Wang, and J. An, "Day-ahead optimization scheduling for islanded microgrid considering units frequency regulation characteristics and demand response," *IEEE Access*, vol. 8, pp. 7093–7102, 2020, doi: 10.1109/ACCESS.2019.2963335.
[20] S. Ahmad, M. M. Alhaisoni, M. Naeem, A. Ahmad, and M. Altaf, "Joint energy management and energy trading in residential microgrid system," *IEEE Access*, vol. 8, pp. 123334–123346, 2020, doi: 10.1109/ACCESS.2020.3007154.
[21] J. Faraji, A. Ketabi, H. Hashemi-Dezaki, M. Shafie-Khah, and J. P. S. Catalao, "Optimal day-ahead self-scheduling and operation of prosumer microgrids using hybrid machine learning-based weather and load forecasting," *IEEE Access*, vol. 8, pp. 157284–157305, 2020, doi: 10.1109/ACCESS.2020.3019562.
[22] J. Faraji, H. Hashemi-Dezaki, and A. Ketabi, "Optimal probabilistic scenario-based operation and scheduling of prosumer microgrids considering uncertainties of renewable energy sources," *Energy Sci. Eng.*, vol. 8, no. 11, pp. 3942–3960, Nov. 2020, doi: 10.1002/ese3.788.
[23] F. Simmini, M. Agostini, M. Coppo, T. Caldognetto, A. Cervi, F. Lain, R. Carli, R. Turri, and P. Tenti, "Leveraging demand flexibility by exploiting prosumer response to price signals in microgrids," *Energies*, vol. 13, no. 12, p. 3078, Jun. 2020, doi: 10.3390/en13123078.
[24] Panan Energy. (2016). *Brasil Lança Programa de Geração Distribuída com Destaque Para Energia Solar*. (in Portuguese). Accessed: Feb. 6, 2021 [Online]. Available: http://www.panamenergy.com.br/noticias/brasil-lanca-programa-de-geracao-distribuida-com-destaque
[25] G. Zanlorenzi, A. L. Szejka, and O. Canciglieri, "Hybrid photovoltaic module for efficiency improvement through an automatic water cooling system: A prototype case study," *J. Cleaner Prod.*, vol. 196, pp. 535–546, Sep. 2018, doi: 10.1016/j.jclepro.2018.06.065.
[26] N. Phuangpornpitak and S. Tia, "Opportunities and challenges of integrating renewable energy in smart grid system," *Energy Procedia*, vol. 34, no. 1, pp. 282–290, 2013, doi: 10.1016/j.egypro.2013.06.756.
[27] H. Turker and P. Favre-Perrod, "Management, optimal sizing and technical-economic analysis of batteries for constant production in photovoltaic systems," in *Proc. IEEE Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Nov. 2016, pp. 1055–1061, doi: 10.1109/ICRERA.2016.7884495.
[28] H. S. V. S. K. Nunna and S. Doolla, "Demand response in smart distribution system with multiple microgrids," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1641–1649, Dec. 2012, doi: 10.1109/TSG.2012.2208658.
[29] J. Byun, I. Hong, and S. Park, "Intelligent cloud home energy management system using household appliance priority based scheduling based on prediction of renewable energy capability," *IEEE Trans. Consum. Electron.*, vol. 58, no. 4, pp. 1194–1201, Nov. 2012, doi: 10.1109/TCE.2012.6414985.
[30] S. Misák, J. Stuchlý, J. Platoy, and P. Krömer, "A heuristic approach to active demand side management in off-grid systems operated in a smart-grid environment," *Energy Buildings*, vol. 96, pp. 272–284, Jun. 2015, doi: 10.1016/j.enbuild.2015.03.033.
[31] M. Zaibi, G. Champenois, X. Roboam, J. Belhadj, and B. Sareni, "Smart power management of a hybrid photovoltaic/wind stand-alone system coupling battery storage and hydraulic network," *Math. Comput. Simul.*, vol. 146, pp. 210–228, Apr. 2018, doi: 10.1016/j.matcom.2016.08.009.
[32] W. El-Baz and P. Tzscheutschler, "Short-term smart learning electrical load prediction algorithm for home energy management systems," *Appl. Energy*, vol. 147, pp. 10–19, Jun. 2015, doi: 10.1016/j.apenergy.2015.01.122.
[33] Y. Ozturk, D. Senthilkumar, S. Kumar, and G. Lee, "An intelligent home energy management system to improve demand response," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 694–701, Jun. 2013, doi: 10.1109/TSG.2012.2235088.
[34] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2166–2173, Dec. 2012, doi: 10.1109/TSG.2012.2201182.
[35] Z. Zhao, W. C. Lee, Y. Shin, and K.-B. Song, "An optimal power scheduling method for demand response in home energy management system," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1391–1400, Sep. 2013, doi: 10.1109/TSG.2013.2251018.
[36] F. Fernandes, T. Sousa, P. Faria, M. Silva, H. Morais, and Z. A. Vale, "Intelligent SCADA for load control," in *Proc. IEEE Int. Conf. Syst., Man Cybern.*, Oct. 2010, pp. 2987–2994, doi: 10.1109/ICSMC.2010.5641983.
[37] LabEEE. (2020). *Building Energy Efficiency Laboratory, Federal University of Santa Catarina (UFSC)*. (in Portuguese). Accessed: Feb. 6, 2020. [Online]. Available: https://labeee.ufsc.br/
[38] COPEL. (2020). *Energy Tariff—Tarifa Convencional—Subgrupo B1*. (in Portuguese). Copel Distribuição. Accessed: Feb. 6, 2020. [Online]. Available: https://www.copel.com/hpcopel/root/nivel2.jsp?endereco=%2Fhpcopel%2Froot%2Fpagcopel2.nsf%2F5d546c6fdeabc9a10325710 00064b22e%2Fc28b22b01ad9182403257488005939bb
[39] COPEL. (2020). *Energy Tariff—Tarifa Branca—Subgrupo B1*. (in Portuguese). COPEL Distribuição S.A. Accessed: Feb. 6, 2020. [Online]. Available: https://www.copel.com/hpcopel/root/nivel2.jsp?endereco=%2Fhpcopel%2Findustrial%2Fpagcopel2.nsf%2Fdocs%2FB0 CA4C8DF4B62F98832581F00058CCF9
[40] A. S. O. Ogunjuyigbe, T. R. Ayodele, and C. G. Monyei, "An intelligent load manager for PV powered off-grid residential houses," *Energy Sustain. Develop.*, vol. 26, pp. 34–42, Jun. 2015, doi: 10.1016/j.esd.2015.02.003.
[41] K. S. Garud, S. Jayaraj, and M. Lee, "A review on modeling of solar photovoltaic systems using artificial neural networks, fuzzy logic, genetic algorithm and hybrid models," *Int. J. Energy Res.*, vol. 45, no. 1, pp. 6–35, Jan. 2021, doi: 10.1002/er.5608.
[42] R. L. Silva, M. Rudek, A. L. Szejka, and O. Canciglieri, "Machine vision systems for industrial quality control inspections," in *Proc. IFIP Int. Conf. Product Lifecycle Manage.*, vol. 540, P. Chiabert, A. Bouras, F. Noël, and J. Ríos, Eds. Cham, Switzerland: Springer, 2018, pp. 631–641, doi: 10.1007/978-3-030-01614-2_58.
[43] M. S. Khani, M. Baneshi, and M. Eslami, "Bi-objective optimization of photovoltaic-thermal (PV/T) solar collectors according to various weather conditions using genetic algorithm: A numerical modeling," *Energy*, vol. 189, Dec. 2019, Art. no. 116223, doi: 10.1016/j.energy.2019.116223.

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