Received: 3 April 2022 | Accepted: 29 May 2022

DOI: 10.1002/int.22942

RESEARCH ARTICLE

WILEY

Electricity production and consumption modeling through fuzzy logic

Lorena M. Olaru[1] | **Arpad Gellert**[1] | **Ugo Fiore**[2] | **Francesco Palmieri**[2]

[1]Department of Computer Science and Electrical Engineering, Lucian Blaga University of Sibiu, Sibiu, Romania

[2]Department of Computer Science, University of Salerno, Fisciano, Salerno, Italy

Correspondence
Arpad Gellert, Department of Computer Science and Electrical Engineering, Lucian Blaga University of Sibiu, Sibiu, Romania.
Email: arpad.gellert@ulbsibiu.ro

Abstract

This paper proposes a prediction model based on fuzzy logic applied to anticipate electricity production and consumption in a building equipped with photovoltaics and connected to the grid. The goal is a smart energy management system able to make decisions and to adapt the consumption to the actual context and to the future electricity levels. The interest is to use as much electricity as possible from own production. The surplus is captured by an energy storage system or is sent to the grid. When no electricity is available from self-production, the grid is used to cover the necessities. The evaluations are performed on a data set collected in a real household. The proposed method is compared in terms of mean absolute error with other existing methods. The method developed based on fuzzy logic has an error of about 67 W, which places it among the most efficient models.

KEYWORDS

electricity prediction, energy management system, fuzzy controller, photovoltaics, smart house

1 | INTRODUCTION

This paper proposes the study of a predictor based on fuzzy logic used for the assessment of energy consumption and energy production in a grid equipped with photovoltaics. Moreover, the purpose of this paper is to introduce a fuzzy controller as a component of an energy management system whose role is decision making with the goal of synchronizing electricity consumption with production.

Among the factors that led to the dramatic energy demand increase in the past decade,[1] population growth, longer time spent inside, higher indoor environment quality with more building functions, and global climate change must be mentioned. Therefore, energy-saving solutions and renewable electricity production from solar, wind, and geothermal energy are necessary. The enormous quantity of solar power makes the use of solar panels to be in great demand and more efficient than alternative sources. According to the US Department of Energy, the quantity of solar light that reaches Earth within an hour and a half is more than sufficient to satisfy the worldwide energy demand for a whole year. Moreover, the cost for a solar panel grid consists only of the installation of its components which means that once installed, the energy resource is free. In time, even the cost of panel acquisition has diminished which would lead to an increase in solar panel users. A couple of years ago, in Germany, the solar panel investments raised significantly due to the grants offered by the state for the solar panel energy supply to the main grid of the country. In this way, the German citizens were encouraged to maximize the annual energy production. While several electricity demand prediction methods have been published,[2,3] targeting schools,[4] campuses,[5] office buildings,[6–8] and hotels,[9] the complex electricity usage patterns in a household make the forecasting more difficult at a small scale due to the individual behaviors.[10]

The study presented in this paper is based on a household from the south of Germany. The collected data comes from two solar panels of 12.24 kWh each and three phases in a house having an energy storage system with a capacity of 8.5 kWh and an energy management system which are presented in more detail by Feilmeier.[11] This paper's objective is to elaborate a system based on fuzzy logic capable of anticipating the energy consumption values and the energy production values with an acceptable error to be used by the energy management system in decision making. Also, we propose an approach based on fuzzy theory to predict the energy consumption and production values which are numerical data that would need to be converted to linguistic fuzzy rules and translated such that a computer system would be able to understand them. The use of fuzzy theory was chosen due to its configuration possibilities and because it allows the user a high degree of implementation freedom. Therewith, the implementation of a fuzzy logic-based system implies a dynamic optimization through the experience gained from trying different system configurations. Usually, this optimization uses the "trial and error" method. Fuzzy theory has been applied before by Li[12] but only for data mining purposes, a neural network is used as the main electricity demand predictor. A combination between fuzzy theory and the seasonal autoregressive fractionally integrated moving average model has been proposed Sadaei et al.[13] In Al-Shanableh and Evcil,[14] a fuzzy interference system was used to predict the per floor annual average electricity consumption of residential buildings based on their climate zone, construction year, house type and number of occupants. In contrast with these fuzzy theory-based approaches, we use our fuzzy controller directly for short-term prediction (5 min, 1 h, or 2 h ahead) of electricity production and consumption in a household.

The rest of this paper is organized as follows. Section 2 provides more information on the use of fuzzy logic in day-to-day life and also on a couple of other predictors used for the anticipation of energy consumption and energy production. Section 3 presents the way the fuzzy theory is applied for the given problem. Section 4 presents the experimental results. Finally, Section 5 deals with the conclusions and future work proposals to further improve the controller.

2 | RELATED WORK

2.1 | Fuzzy theory application

Applying fuzzy theory in a control application is known as a fuzzy controller. The fuzzy controller is a technology in a continuous evolution that can improve the industrial automation capabilities and it is fit for the control tasks conducted in general in programmable controllers such as PCs.

Moreover, due to the fact that the fuzzy controller allows multivalue inputs, and it is not narrowed by statements such as “true” or “false”, it can be used in empirical expertize by specifying what action must be taken according to the given input. This type of controller is used both in small and simple applications and in complex and sophisticated projects. Its portability depends on the way of programming and also on the system characteristics on which we want to apply the fuzzy control.

The fuzzy theory is used in a variety of domains such as the aerospace industry for the altitude control of a plane or the control of a satellite, the automotive industry for the speed control or for the control of smart systems used on the highway to enhance the automatic transmission, the business industry where it is used in decision support systems or in personnel evaluation systems in a big firm, in the defense sector for underwater target recognition or for the automatic infrared image recognition, in the food industry for the production process of milk or cheese, in medical diagnostic support systems or in modeling the neuropathological discoveries in patients with Alzheimer and the list goes on. Moreover, it can be combined with other methods such as neural networks to enhance artificial intelligence systems. Some examples come from Baloglu and Demir[15] and Walter and Gomide[16] where fuzzy technology has been exploited in agent-based systems.

More and more people from the industry and the academic sector feel the need to explore the benefits of fuzzy logic and the associated technologies. The fuzzy logic can be used when the conventional technologies are not enough for systems or devices whose behavior cannot be described with mathematical methods or systems that show significant uncertainties or contradictory conditions. One of the most famous applications of fuzzy logic is the antilock braking system which can be found in most of modern cars. The rules used in such a system can make use of the speed of the vehicle, the pressure and the temperature of the braking system, the angle of side movement and the forward movement of the car.

Zadeh,[17] the father of fuzzy theory, tries to answer the following question: “Is there a need for fuzzy logic?” He states that fuzzy logic is a way of formalizing two of the most remarkable human abilities. First of all, the ability to converse, to reason and to make rational decisions in an uncertain and imprecise environment, with a lack of information or based on conflictual information, to be more clear, in an imperfect information environment. Second, the ability to run various physical and mental tasks without computation or measurement. Zadeh also states that the linguistic variable mechanism is unique in fuzzy logic and it has a very important role in the design and conception of the control systems and the user products. Another important thing that fuzzy logic might offer is the big universality compared to bivalent logic. He ends the article by saying that fuzzy logic is much more than a simple logic system.

2.2 | Alternative prediction methods for electricity production and consumption

Since the electricity industry recently (in the last decade) went through a significant modernization process, its infrastructure has also been updated. This led to a more volatile and less predictable offer, demand, and also prices. The energy prediction problem is essential for managing, monitoring, and optimizing (the efficiency and cost) in different energy systems such as the energy production system (wind power, solar power, batteries) or the consumer. Prediction, in general, is presented by Gellert and Florea,[18] as the estimation of future states based on the current and eventually previous states. There are many studies regarding the topic of predicting electricity production and consumption. Many of these studies focus on larger areas or on an entire country, while the smaller networks or the micro-grids are becoming a more recent research topic.

Feilmeier[11] studies an energy management system in a household equipped with solar panels, energy storage, and an energy management system. The author uses a series of tools to receive the data from the FENECON Energy Management System (FEMS) and transmit them further to the neural network-based predictor. This type of predictor was chosen because of its feasibility. The success of the predictor consists of the data characteristics on which the prediction is based, in this case, it could be either the season, the part of the day, the weather or even the family's planned vacations. A prior classification and filtration of the data is recommended before being processed by the predictor. The data sets collected by Feilmeier[11] have been used to evaluate several predictors of different types, namely: a multilayer perceptron (MLP),[11] a Markovian predictor,[19] a predictor based on long short-term memory (LSTM),[20] a predictor based on a variation of the ARIMA algorithm[21,22] and a predictor based on the TBATS algorithm.[22]

Gellert et al.[19] compared a context-based predictor (Markovian predictor), an incremental predictor and a hybrid predictor (which combines the functionalities of both the Markovian and the incremental predictors). After running the simulations on all the three configurations and analyzing the results, the authors concluded that the incremental predictor does not fit the data set. Instead, the Markovian predictor and the hybrid one had better results, the best one being the one based on the Markov model with a mean absolute error smaller than the one of the MLP predictor. The best configuration for such a system would have a history length of 100, a context consisting of a single value, and an interval of size one. The role of the predictor is to balance the production and consumption of electricity, to increase self-consumption, decreasing in this way the pressure on the grid.

Statistical prediction of electricity production and consumption has been evaluated by Gellert et al.[22] The ARIMA-based predictor had better results than the MLP but worse than the Markov model. This prediction method is more complex in terms of execution time and difficulty of computation. It is worth mentioning that one of the most powerful countries in the world, China, uses a variation of the ARIMA algorithm as one of the main energy consumption prediction methods on a national level. The TBATS-based predictor has better output than the MLP and ARIMA models, but worse than the Markovian predictor. The authors chose this prediction method for its general character and its ability to determine seasonal patterns from the processed time series.

LSTM is a recurrent neural network and was exploited to predict electricity production and consumption by Bachici and Gellert.[20] LSTM has a memory component that transmits the information learned at the current timestep to the next timesteps. It is able to forget unnecessary information from the preceding state, forwarding only the relevant parts of the state to the output. For nonlinearity, the LSTM is applying activation functions, the sigmoid function being used by Bachici and Gellert[20] with output between 0 and 1. The experiments have shown that the LSTM configured optimally for the electricity prediction task has four inputs, 10 first hidden layer neurons, 5 second hidden layer neurons, a learning rate of 0.01 and 50 epochs. The LSTM was weaker in terms of accuracy than the Markov and TBATS models, but far better than the MLP and ARIMA. MLPs have also been applied for short-term forecasting of the total power consumption at building level by Escrivá-Escrivá et al.[23] An important input applied to the MLP was the day type. To predict the electricity consumption on a certain day, the MLP was trained using days of the same type with similar weather characteristics (temperature coefficient). The model has been evaluated at the University of Valencia, an institution with over 60 buildings and an electricity consumption of around 11.5 MW. A hybrid method combining LSTM and MLP was presented by Zhang et al.[24]

Kim and Cho,[25] applied a convolutional neural network (CNN) together with an LSTM to forecast residential electricity consumption. This hybrid method is able to recognize electricity consumption features. The CNN component can determine the features that influence consumption. The output of the CNN is then used as input by the LSTM able to determine irregular electricity consumption trends. The output of the LSTM is used by a fully connected layer which returns the final prediction. A similar methodology is used by Le et al.[26] with bidirectional LSTM. Cai et al.[27] analyzed gated CNNs for day-ahead electricity consumption prediction in a building and compared them with the SARIMAX model. In their experiments, the gate CNNs proved to be better. Bedi et al.[28] proposed an Elman neural network and an exponential model to predict electricity consumption in IoT-driven buildings. The authors exploited the correlation of the electricity consumption with the ambient temperature and the building's occupancy, respectively. A laboratory with smart monitoring and control was used in their experiment.

Fumo and Biswas[29] proposed linear regression and quadratic regression models to predict hour- and day-ahead electricity consumption in residential buildings. The authors observed that a larger interval between observations improved the quality of the linear regression model, which thus was better for day-ahead electricity prediction. On the other hand, the quadratic regression model was better for shorter intervals, being efficient for hour-ahead electricity prediction. Several other machine learning methods have been applied for short-term electricity consumption forecasting at the building level: a data-driven swarm intelligence-based ensemble model by Li et al.,[30] a method based on rough set theory and deep learning algorithms by Lei et al.,[31] linear kernel-based algorithms and tree model-based algorithms by Ding et al.[32] and a Bayesian regression model by Dab et al.[33] Finally, a deep generative model based on a latent stochastic recurrent neural network for predicting the electricity generation demand of large-scale hydropower stations has been presented by Zhou et al.[34] It also leverages generative flows for approximating the time series' distribution.

3 | APPLYING FUZZY LOGIC TO ESTIMATE ELECTRICITY PRODUCTION AND CONSUMPTION

The main focus of this paper is to present a model based on fuzzy logic that would work as a controller in a smart energy management system. Its purpose would be to predict the production and consumption electricity values in a household linked to a grid that uses green energy such as solar energy through solar panels. The following steps are to be covered for a functional model: taking the input data from FEMS, processing the input data through fuzzy logic, reading the output data provided by the fuzzy controller.

We used the data collected by Feilmeier[11] within a household consisting of an energy storage system (a lithium-ion battery with a capacity of 8.5 kWh) connected to two solar panels (denoted PV1 and PV2) and three phases (denoted Ph1, Ph2, and Ph3). In Figure 1 the energy storage system diagram is presented with all its components. The phases also connected to the main grid are bidirectional which means that the main grid can provide energy to the household through the storage system, or it can be powered by the surplus electricity produced by the solar panels also through the storage system. The solar panels are not a continuous energy source, being dependent on outside factors such as the weather, the time of day or the season. Thus, during the night, the solar panels do not produce any electricity and if there are active consumers and the battery runs low, the electricity would be provided by the main grid. The same scenario can occur during rainy or cloudy days or during the winter, when solar power is reduced. This is the reason why there is a need for energy management systems to predict both the consumption and production of electricity for efficient management.

According to Figure 2, the fuzzy controller consists of four different modules or blocks: the fuzzification block, the inference engine, the rule base and the defuzzification block. Each module has its own set of tasks, and they are all linked together to offer a result at the exit of the controller.

This article follows the steps presented by Wang and Mendel[35] who provided a generic method of generating fuzzy rules from numerical data. The first step consists of dividing the input and output data from the numerical data into fuzzy regions. This step is done in the

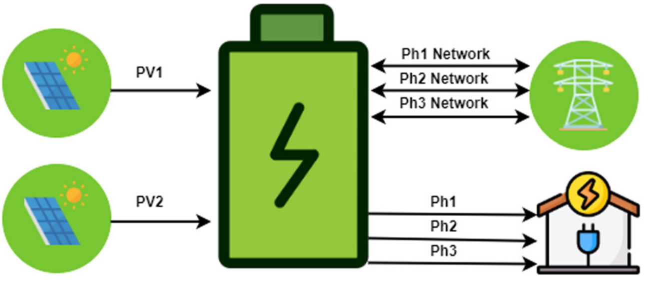

FIGURE 1 The energy storage system diagram [Color figure can be viewed at wileyonlinelibrary.com]

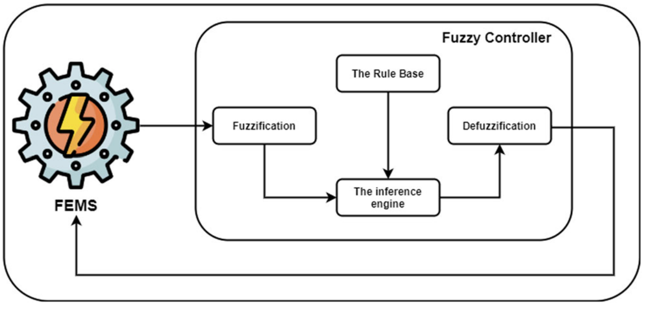

FIGURE 2 The structure of the fuzzy controller [Color figure can be viewed at wileyonlinelibrary.com]

fuzzification block, and it is part of the preprocessing of the data. Also, the fuzzification block will generate fuzzy rules from the data obtained in the previous step.

Fuzzification is the method through which the input data is transformed into fuzzy sets. The input data are real, crisp values measured by the sensors of the energy management system. These values are preprocessed to be interpretable by the fuzzy system. This kind of transformation makes use of a membership function that maps each input value to a membership degree between 0 and 1. The mapping space is uniquely divided according to the function used. The most used membership functions (see Figure 3) are the triangular, the trapezoidal, and the Gaussian.[36]

For the prediction of energy production and consumption values, the triangular membership function was chosen, and the data domain was split into triangular fuzzy regions. The step of the regions varies as the numerical data increases because of the data dispersion. Analyzing the values from the data sets it could be seen that there was not a uniform distribution which means that in some ranges where we had a higher frequency of data, the step would be smaller and therefore a higher number of fuzzy regions and where the frequency of data was lower, we would have a bigger step and therefore a smaller number of fuzzy regions. The challenge is to find the optimal partitioning of the working domain. Figure 4 describes how the domain was divided into fuzzy regions for our problem. With values from 0 going up to 6564.6, we obtained 1161 fuzzy regions.

Once the fuzzy regions are determined and the fuzzy rules are generated, the Fuzzy Rule Base is created. It is an *N*-dimensional space where *N* represents the number of input data. For

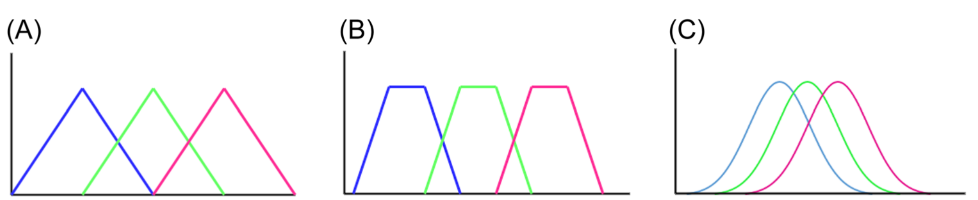

FIGURE 3 Membership functions (A) triangular; (B) trapezoidal; (C) Gaussian. [Color figure can be viewed at wileyonlinelibrary.com]

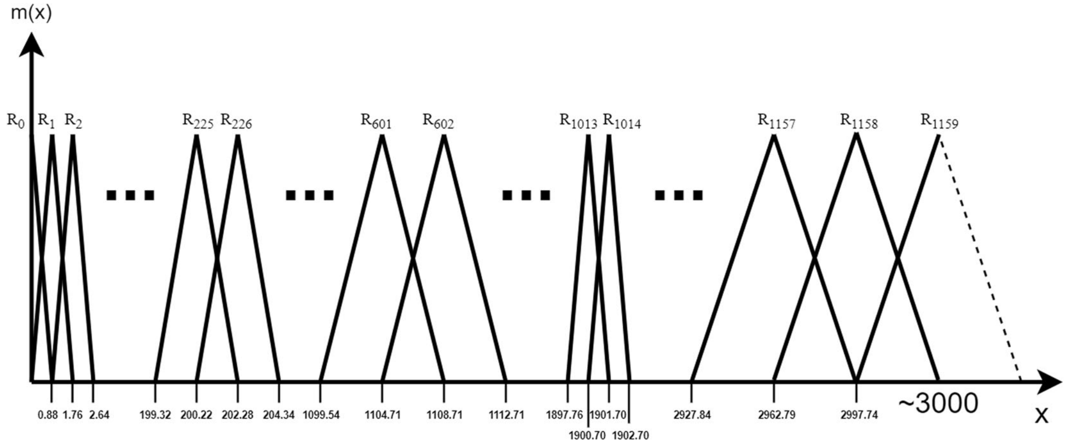

FIGURE 4 Numerical domain divided into fuzzy regions

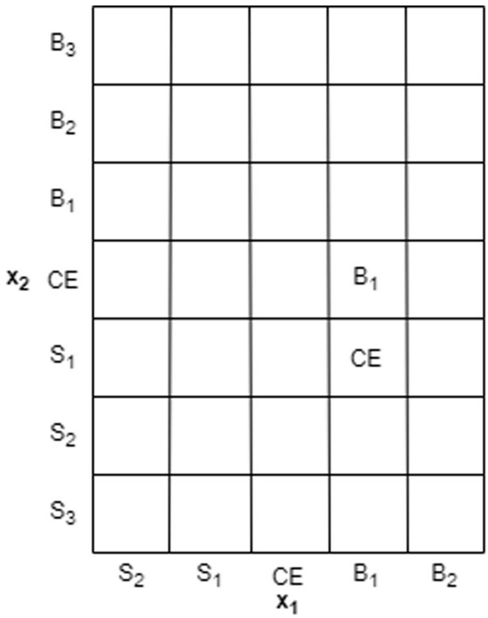

FIGURE 5 The form of a Fuzzy Rule Base

a system with two inputs and one output ($x_1, x_2; y$) and "AND" rules, the Rule Base can be represented as a matrix as shown in Figure 5.

Two rules were used as an example in the matrix. They are structured as follows: "R_1: IF x_1 is B_1 and x_2 is S_1, THEN y is CE" and "R_2: IF x_1 is B_1 and x_2 is CE, THEN y is B_1." The lines represent the regions corresponding to input x_1 and the columns represent the regions corresponding to input x_2. For each rule, the regions of interest need to be identified and the determined position will be marked with the region corresponding to the output. At this phase, conflicts can appear between the rules already mapped and the new generated rules. If this happens, developing a method of measuring the trust in that rule could be helpful and depending on the degree of trust, the more trusting rule should have a place in the matrix.

The next step would be finding the rules that would generate the output of the system. The defuzzification strategy for the pair of input values (x_1, x_2) consists of combining the last fuzzy rules using the multiplication operation to determine the output corresponding to the given input. As an example, $m^i_{o^i} = x_{I^i_1}(x_1) * x_{I^i_2}(x_2)$, where o^i is the output region of rule i, whereas I^i_j represents the input region of rule i for the component j. The rules are chosen by applying the input data onto every rule in the Fuzzy Rule Base. Thereby, if we have N rules in the rule base, it will generate N mappings, each one representing the membership degree of the input data to the rule. Figure 6 depicts an example of mapping the input data onto two rules. Taking into consideration the set of inputs (temperature: 16.5, wind speed: 11.8), we can observe how the inputs are mapped on both rules and so for R_1 the membership degree of the temperature has a value of 0.3 and the membership degree for the wind has a value of 0.8, whereas R_2 presents the temperature input with a membership degree of 0.3 and the wind has a membership degree value of 0.2. Fuzzy operators are used to determine the result of each mapping. The most common ones for "OR" and "AND" rules are the min and max operators. Finally, all the results

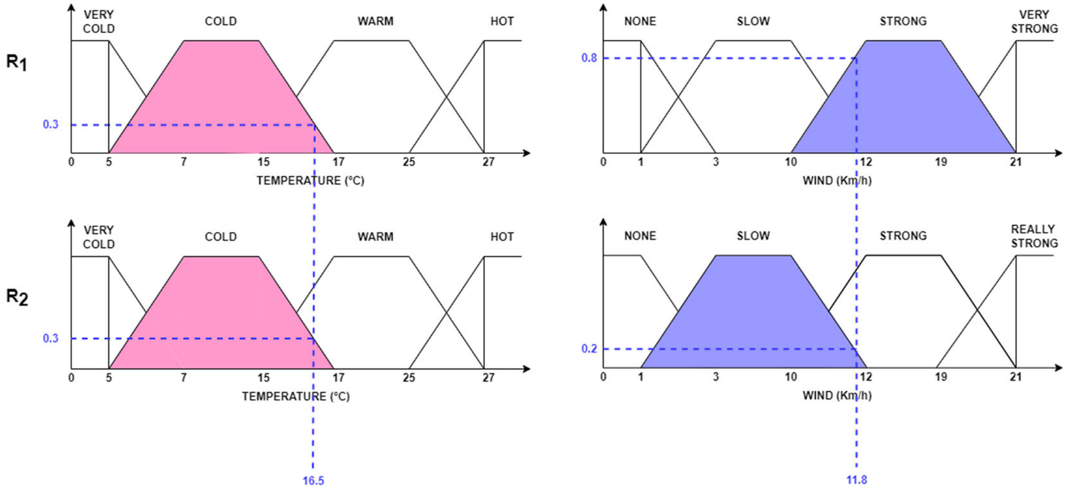

FIGURE 6 Input data mapping onto fuzzy rules [Color figure can be viewed at wileyonlinelibrary.com]

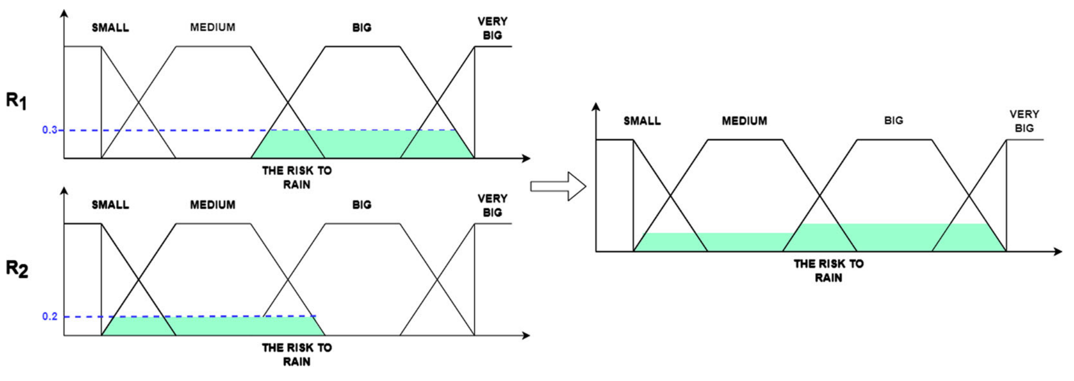

FIGURE 7 The result of the inference [Color figure can be viewed at wileyonlinelibrary.com]

are combined through the inference engine. It uses an inference method to compute all the mapping results and to determine the defuzzification area.

For the previous example, the MIN method was used to determine the results of each rule. This method implies choosing the smallest membership degree mapped on that rule. To compute the final area, we used the maximum algorithm which implies the reunion of the areas determined beforehand. This whole process is called inference and, in the end, the final result, which can be seen in Figure 7, is a fuzzy value. The next step is to defuzzify this fuzzy value into a real value.

There are several defuzzification methods that can be used to process the output of the inference block. There is no method that would work on all the systems so it can be one of the configurable parameters of the system to find the best match. The most popular ones are the mean of maxima method, the weighted fuzzy mean method, and the centroid method.

Using this five-step system, we end up choosing the fuzzification method, the membership function, the type of inference, and the defuzzification method. To find the best configuration of the system, we need to analyze each output and change the parameters with the most suitable ones. Also, each block is linked to one another so a change in one block may affect the results of another one.

4 | EXPERIMENTAL RESULTS

The input data provided by FEMS covers up to a period of 5 months from January 1, 2015, to May 31, 2015. The primitive data consists of a timestamp and the value measured. Each consumer and producer has its own data set on which the controller was tested. The consumption and production values were measured at a periodicity of 5 min.

4.1 | Methodology

The first step toward simulation is setting the configurable parameters. These parameters are passed to the fuzzy controller to form the configuration on which it will run. The configurable parameters are the following: the number of training values, the number of inputs for the fuzzy rule, the method to solve the conflicts generated by the rule base and the defuzzification method. If the counter method is used to solve the conflicts in the rule base, then two more parameters need to be configured: the error threshold and the upper limit of the counter. The number of training values translates as the number of values from the data set used to train the controller. During the training stage, the first version of the rule base is created upon which the first predictions will be made. The number of inputs represents the number of values the fuzzification block will receive as input. It is also used to determine the size of the fuzzy data set, the structure of a fuzzy rule (n-inputs, one output), the structure of the rule base (it is an n-dimensional structure), and so on. The threshold and the upper limit of the counter decide which rule wins the place in the rule base and which not in case of a conflict. Upon each prediction, the difference between the predicted value and the real value from the data set is computed. If the difference between those two is below the threshold, then the confidence in the rules used at prediction is increased. Otherwise, the confidence (the rule counter) will be decreased.

The domain division into fuzzy regions is the most important step of the process. It can even define the success of the whole controller. For this step, the distribution of data (see Figure 8) must be taken into consideration and for our application we created different divisions for each data set. The number of fuzzy regions in a subdomain is directly proportional to the number of values in that subdomain. Next, two diagrams depict the way the step of the fuzzy regions influences the controller's error. The aim was to find the step which gives the best results for the mean absolute error (as small as possible, see Figure 9) and also the number of predictions made by rules (as big as possible, see Figure 10). An interesting fact is that during the simulations, we found two or more different steps for which the controller offered the same output. Fuzzy region distribution influences both the rule creation and the defuzzification step where the fuzzy area is computed.

The controller needs an initial set of rules to be able to predict output values. After each prediction, a new rule is created using the last input data and the real value that was supposed to be predicted. The initial set of rules is created using a certain number of training values from the data set. In Figure 11 it can be seen that the mean absolute error does not necessarily rely on the size of the training set.

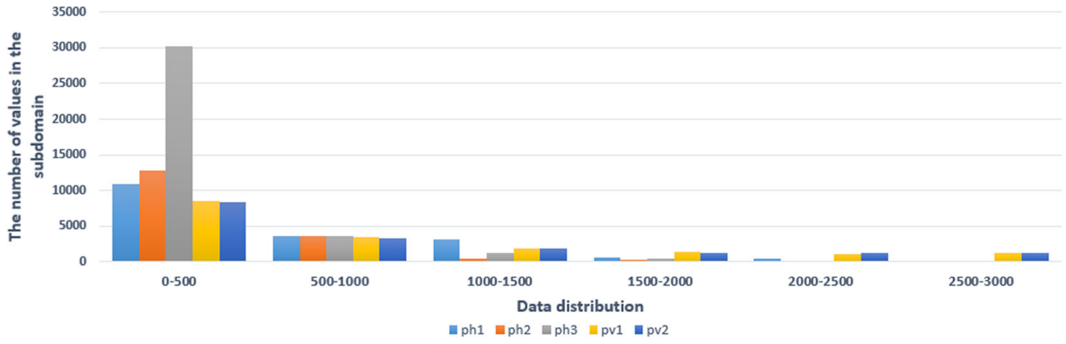

FIGURE 8 Data distribution on the [0, 3000] interval [Color figure can be viewed at wileyonlinelibrary.com]

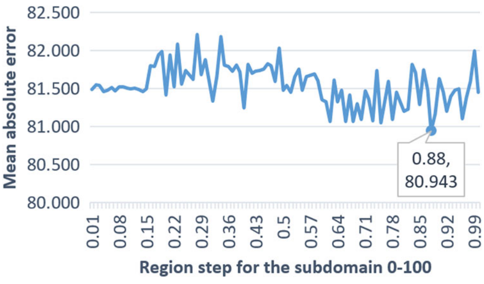

FIGURE 9 The influence of the step on the mean absolute error [Color figure can be viewed at wileyonlinelibrary.com]

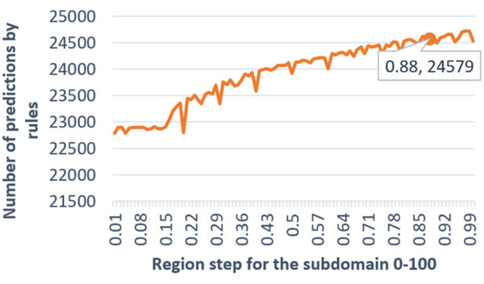

FIGURE 10 The influence of the step on the number of predictions [Color figure can be viewed at wileyonlinelibrary.com]

It can be seen that the controller does not need more than 25 values in the training set to be able to predict values with an error as small as possible. Moreover, as the training set is bigger, the number of predicted values is smaller and so the error increases. Once a parameter is chosen, it is fixed to configure the other ones.

The next parameter to be configured was the number of inputs, varied from 2 up to 10. In the diagrams it can be seen how this variation influences the mean absolute error and the number of predictions made through fuzzy rules. Looking at the average error (see Figure 12) and the number of predictions (see Figure 13), the best results were obtained by using three inputs. The more the number of inputs increases, the harder it is to predict an output through fuzzy rules. This happens because the benchmarks used do not have long patterns, which

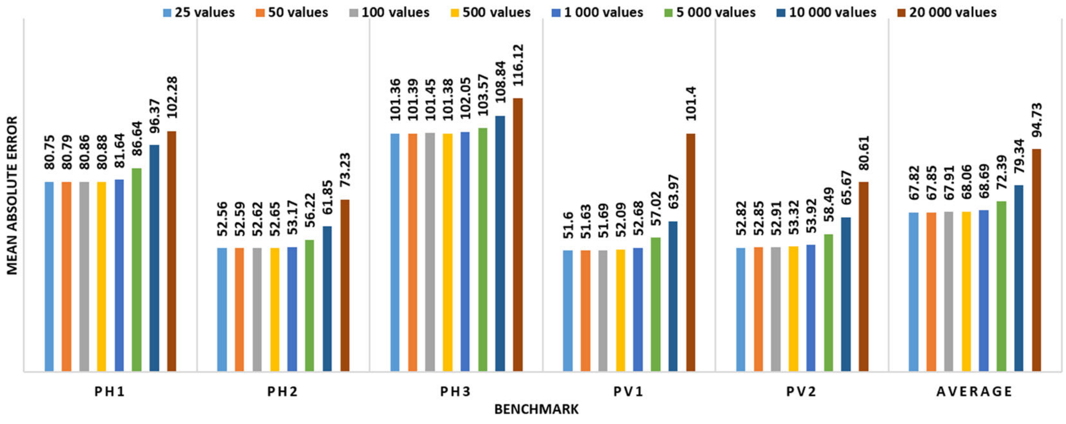

FIGURE 11 The influence of the number of training values on the mean absolute error [Color figure can be viewed at wileyonlinelibrary.com]

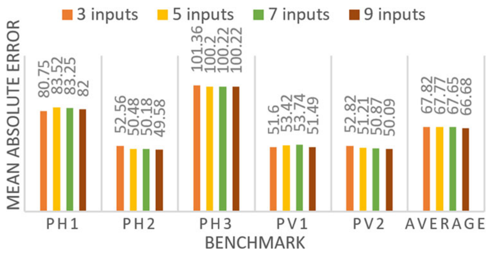

FIGURE 12 The influence of the number of inputs on the mean absolute error [Color figure can be viewed at wileyonlinelibrary.com]

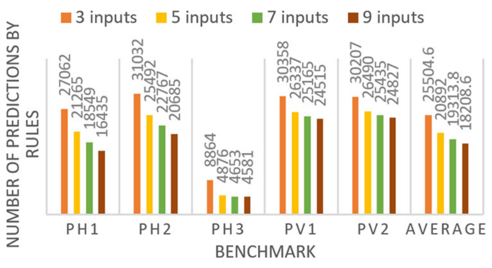

FIGURE 13 The influence of the number of inputs on the number of predictions [Color figure can be viewed at wileyonlinelibrary.com]

means that a series of 10 consecutive values from the data set is unlikely to repeat itself with small variations from the initial region set.

For the Fuzzy Rule Base and the conflicts that can appear while introducing a new rule, three methods were simulated: using the last generated rule, using the rule with the greatest membership degree, and using saturated counters that describe the confidence in each rule. The first method had the worst results with a significantly increased final error, in contrast to the other two which had somewhat similar results, but the counter-based method was slightly better. We chose to continue with the saturated counters methods which imply configuring an error threshold and the

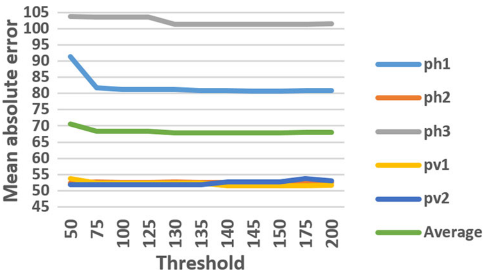

FIGURE 14 Varying the error threshold [Color figure can be viewed at wileyonlinelibrary.com]

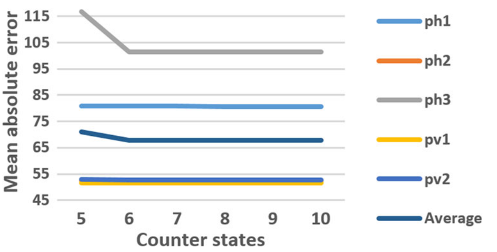

FIGURE 15 Varying the number of counter states [Color figure can be viewed at wileyonlinelibrary.com]

number of counter states. Figures 14 and 15 show the influence of these two parameters. As the results state, neither of them has much impact on the outputs: there is no need for more than nine states for the counter and no need for a higher threshold than 145.

The last parameter to be configured was the defuzzification method for which three possibilities were chosen: the centroid method, the mean of maxima method and the weighted fuzzy mean method. All these methods had very similar results, but the centroid method has the highest precision.

4.2 | Evaluation

After all the parameters were set, we compared the predicted values with the actual values from the data set (see Figure 16). The comparison was made over a period of 3 days, on the PV1 data set which contains data from one of the three phases connected to the main network. The mean absolute error for these 3 days is 11.23. It can be seen that the prediction line closely follows the real values line.

The mean absolute error obtained on the whole period on all the data sets was 67.82. This best fuzzy controller configuration is compared with existing prediction methods in Figure 17.

As Figure 17 shows, the fuzzy controller (67.82) is outperformed only by the Markov model (34.42) and it is better than all the other evaluated forecasting methods: MLP (211.07), ARIMA (198.27), TBATS (73.62), and LSTM (100.77).

The better results achieved by the Markov model can be the effect of its context-awareness, with situations met earlier in the history window being dealt with very well. On the other hand, the fuzzy controller is using the whole history mapped into fuzzy rules. Spikes in the data sets can influence the behavior of the fuzzy controller and slightly degrade performance.

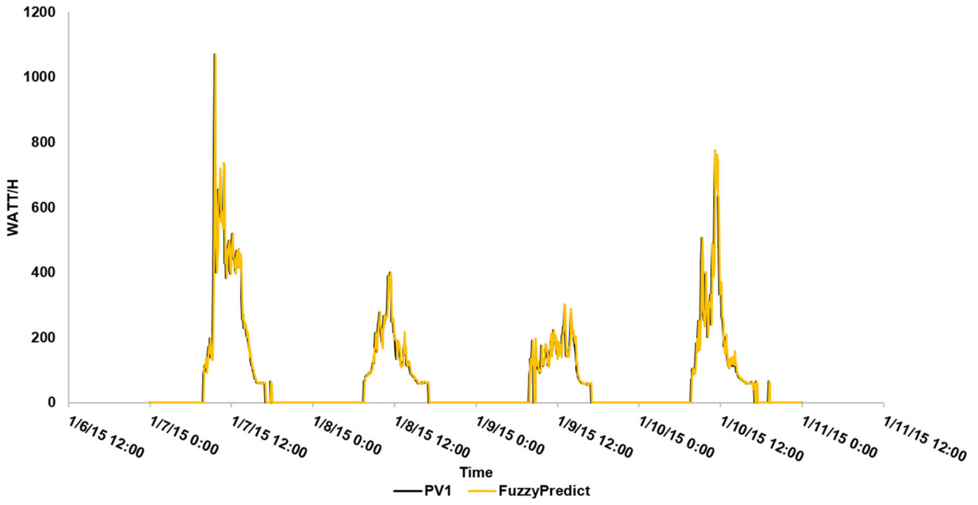

FIGURE 16 The prediction compared with the real values on the PV1 data set [Color figure can be viewed at wileyonlinelibrary.com]

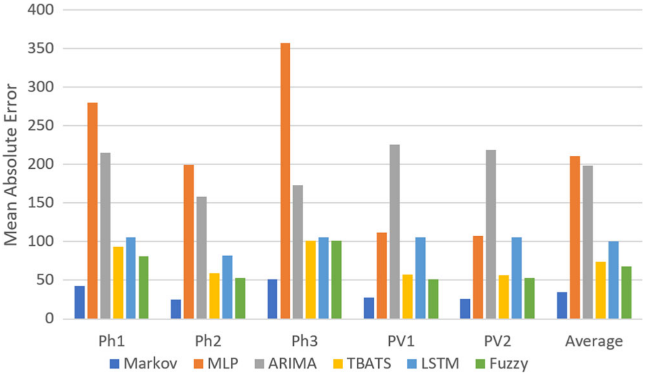

FIGURE 17 The mean absolute error measured using different forecasting models [Color figure can be viewed at wileyonlinelibrary.com]

5 | CONCLUSIONS AND FURTHER WORK

The energy prediction domain is continuously growing and in need of new and adaptive methods necessary to the energy management systems that keep evolving due to the high constant need for resources. Photovoltaic panels are a source of renewable energy and consist of a big part of the energy producers on a global scale. That is why there is a constant search for the optimal method of energy management in the same context as the one presented in this paper or even on a bigger scale. This paper's objectives were to present a fuzzy rule-based controller that could be incorporated into such a system.

Fuzzy theory allows the user the liberty to choose the optimal configuration based on the experience gained in the implementation of the system based on this theory. Basically, there is no base configuration or a standard one. The implemented system needs to closely monitor the problem to be solved to have the best results.

The controller presented in this paper has been adapted to the environment in which it is intended to be used. The starting point was the basic steps of building such a system presented by Wang and Mendel.[35] After the structure was determined, a set of configurable parameters was defined, and multiple simulations were made. Following the analysis of the simulation results on different configurations, a set of optimal parameters was found for the data sets generated by FEMS. This set consists of using three inputs in a rule, providing 25 training values, using the saturated counters method with nine states to solve the possible conflicts in the rule base, using the centroid method for converting the fuzzy values into real values and using an error threshold of 145 based on which the rule confidence will increase or decrease. This configuration resulted in an average on all the data sets of the mean absolute error of 67.82, while the predictor based on the ARIMA model and the MLP resulted in an error equal to 198.27, respectively, 211.07. It was also better than the TBATS and LSTM models, whose errors were 73.62 and 100.77, respectively. The error of the fuzzy controller was mainly influenced by the results obtained from the phase data sets Ph1, Ph2 and Ph3, since the data there represents the consumed energy which is harder to predict. Moreover, the data from these data sets is not uniformly distributed which creates challenges in prediction.

Because the data sets are not all similar even though they represent the same category of data, as further work we propose generating a membership function that would be able to map the fuzzy regions to the benchmark data using information such as data distribution on the fuzzy domain. Thereby, each benchmark would be characterized by its own regions which would lead to higher accuracy of prediction. Another future development would be the use of different inference algorithms in the presented controller.

ACKNOWLEDGMENT

Open Access Funding provided by Universita degli Studi di Salerno within the CRUI-CARE Agreement.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon request.

ORCID

Lorena M. Olaru http://orcid.org/0000-0003-2997-2770
Arpad Gellert http://orcid.org/0000-0002-5482-967X
Ugo Fiore http://orcid.org/0000-0003-0509-5662
Francesco Palmieri http://orcid.org/0000-0003-1760-5527

REFERENCES

1. Cao X, Dai X, Liu J. Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade. *Energy Build*. 2016;128:198-213.
2. Bourdeau M, Zhai X, Nefzaoui E, Guo X, Chatellier P. Modeling and forecasting building energy consumption: a review of data-driven techniques. *Sustain Cities Soc*. 2019;48:101533.
3. Ahmad T, Zhang H, Yan B. A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. *Sustain Cities Soc*. 2020;55:102052.

4. Mohammed A, Alshibani A, Alshamrani O, Hassanain M. A regression-based model for estimating the energy consumption of school facilities in Saudi Arabia. *Energy Build*. 2021;237:110809.
5. Kim MK, Kim YS, Srebric J. Predictions of electricity consumption in a campus building using occupant rates and weather elements with sensitivity analysis: artificial neural network vs. linear regression. *Sustain Cities Soc*. 2020;62:102385.
6. Ilbeigi M, Ghomeishi M, Dehghanbanadaki A. Prediction and optimization of energy consumption in an office building using artificial neural network and a genetic algorithm. *Sustain Cities Soc*. 2020;61:102325.
7. Skomski E, Lee J-Y, Kim W, Chandan V, Katipamula S, Hutchinson B. Sequence-to-sequence neural networks for short-term electrical load forecasting in commercial office buildings. *Energy Build*. 2020;226:110350.
8. Dong Z, Liu J, Liu B, Li K, Li X. Hourly energy consumption prediction of an office building based on ensemble learning and energy consumption pattern classification. *Energy Build*. 2021;241:110929.
9. Shao M, Wang X, Bu Z, Chen X, Wang Y. Prediction of energy consumption in hotel buildings via support vector machines. *Sustain Cities Soc*. 2020;57:102128.
10. Falaki F, Merabtine A, Martouzet D. A spatio-temporal analysis of electric appliance end-use demand in the residential sector: case study of tours (France). *Sustain Cities Soc*. 2021;65:102635.
11. Feilmeier S. *Loads management based on photovoltaic and energy storage system*. MSc Thesis. "Lucian Blaga" University of Sibiu; 2015.
12. Li C. A fuzzy theory-based machine learning method for workdays and weekends short-term load forecasting. *Energy Build*. 2021;245:111072.
13. Sadaei HJ, Guimarães FG, daSilva CJ, Lee MH, Eslami T. Short-term load forecasting method based on fuzzy time series, seasonality and long memory process. *Int J Approx Reason*. 2017;87:196-217.
14. Al-Shanableh F, Evcil A. Prediction of energy consumption of residential buildings in Northern Cyprus using fuzzy interference system. *Energy Build*. 2022;256:111555.
15. Baloglu UB, Demir Y. An agent-based Pythagorean fuzzy approach for demand analysis with incomplete information. *Int J Intell Syst*. 2018;33(5):983-997.
16. Walter I, Gomide F. Genetic fuzzy systems to evolve interaction strategies in multiagent systems. *Int J Intell Syst*. 2007;22(9):971-991.
17. Zadeh LA. Is there a need for fuzzy logic? *Inform Sci*. 2008;178(13):2751-2779.
18. Gellert A, Florea A. Investigating a new design pattern for efficient implementation of prediction algorithms. *J Digital Inform Manage*. 2013;11(5):366-377.
19. Gellert A, Florea A, Fiore U, Palmieri F, Zanetti P. A study on forecasting electricity production and consumption in smart cities and factories. *Int J Inform Manage*. 2019; 49: 546-556.
20. Bachici M-A, Gellert A. Modeling electricity consumption and production in smart homes using LSTM networks. *Int J Adv Stat IT&C Econ Life Sci*. 2020;X(1):80-90.
21. Barbu P. Forecasting electricity consumption and production using ARIMA time series models. MSc Thesis. "Lucian Blaga" University of Sibiu; 2019.
22. Gellert A, Fiore U, Florea A, Chis R, Palmieri F. Forecasting electricity consumption and production in smart homes through statistical methods. *Sustain Cities Soc*. 2022;76:103426.
23. Escrivá-Escrivá G, Álvarez-Bel C, Roldán-Blay C, Alcázar-Ortega M. New artificial neural network prediction method for electrical consumption forecasting based on building end-uses. *Energy Build*. 2011;43(11):3112-3119.
24. Zhang C, Li J, Zhao Y, Li T, Chen Q, Zhang X. A hybrid deep learning-based method for short-term building energy load prediction combined with an interpretation process. *Energy Build*. 2020;225:110301.
25. Kim T-Y, Cho S-B. Predicting residential energy consumption using CNN-LSTM neural networks. *Energy*. 2019;182:72-81.
26. Le T, Vo MT, Vo B, Hwang E, Rho S, Baik SW. Improving electric energy consumption prediction using CNN and Bi-LSTM. *Appl Sci*. 2019;9(20):4237.
27. Cai M, Pipattanasomporn M, Rahman S. Day-ahead building-level load forecasts using deep learning vs. traditional time-series techniques. *Appl Energy*. 2019;236:1078-1088.
28. Bedi G, Venayagamoorthy GK, Singh R. Development of an IoT-driven building environment for prediction of electric energy consumption. *IEEE Internet Things J*. 2020;7(6):4912-4921.

29. Fumo N, Biswas MAR. Regression analysis for prediction of residential energy consumption. *Renew Sustain Energy Rev*. 2015;47:332-343.
30. Li K, Tian J, Xue W, Tan G. Short-term electricity consumption prediction for buildings using data-driven swarm intelligence based ensemble model. *Energy Build*. 2021;231:110558.
31. Lei L, Chen W, Wu B, Chen C, Liu W. A building energy consumption prediction model based on rough set theory and deep learning algorithms. *Energy Buildings*. 2021;240:110886.
32. Ding Y, Fan L, Liu X. Analysis of feature matrix in machine learning algorithms to predict energy consumption of public buildings. *Energy Build*. 2021;249:111208.
33. Dab K, Agbossou K, Henao N, Dubé Y, Kelouwani S, Hosseini SS. A compositional kernel based Gaussian process approach to day-ahead residential load forecasting. *Energy Build*. 2022;254:111459.
34. Zhou F, Wang Z, Zhong T, Trajcevski G, Khokhar A. HydroFlow: towards probabilistic electricity demand prediction using variational autoregressive models and normalizing flows. *Int J Intell Syst*. Forthcoming 2022.
35. Wang L-X, Mendel JM. Generating fuzzy rules by learning from examples. *IEEE Trans Syst Man Cybernet*. 1992;22(6):1414-1427.
36. Mendel JM. Fuzzy logic systems for engineering: a tutorial. *Proc IEEE*. 2019;83(3):345-377.

How to cite this article: Olaru LM, Gellert A, Fiore U, Palmieri F. Electricity production and consumption modeling through fuzzy logic. *Int J Intell Syst*. 2022;37:8348-8364. doi:10.1002/int.22942