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POWER SYSTEMS AND POWER ELECTRONICS

The application of the fuzzy rule-based Bayesian algorithm to determine which residential appliances can be considered for the demand response program

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Abstract. This paper proposes the usage of the fuzzy rule-based Bayesian algorithm to determine which residential appliances can be considered for the Demand Response program. In contrast with other related studies, this research recognizes both randomness and fuzziness in appliance usage. Moreover, the input data for usage prediction consists of nodal price values (which represent the actual power system conditions), appliance operation time, and time of day. The case study of residential power consumer behavior modeling was implemented to show the functionality of the proposed methodology. The results of applying the suggested algorithm are presented as colored 3D control surfaces. In addition, the performance of the model was verified using R squared coefficient and root mean square error. The conducted studies show that the proposed approach can be used to predict when the selected appliances can be used under specific circumstances. Research of this type may be useful for evaluation of the demand response programs and support residential load forecasting.

Key words: demand response; residential power consumers; uncertainty; fuzzy rule-based Bayesian.

1. INTRODUCTION

The power system sector is currently undergoing significant changes. There is an increasing interest in Smart Grids, environmental protection, and the energy crisis. These aspects make residential power consumers getting more aware of the strong ties between the power industry and the economy. Growing electricity costs are often the reasons behind changing the existing habits of using household appliances. It is desirable to meet the needs of clients while taking into account the current operating conditions of the power system [1]. Different types of factors are designed to properly influence electricity consumers under the demand response (DR) mechanism. These may be, for example, appropriate tariffs or special discounts. In the presented study it was assumed that the value of the nodal price (LMP – locational marginal price) was the external factor stimulating electricity consumption. The change from traditional tariffs in favor of nodal prices may contribute to the consumer's increased awareness that the cost of generating and delivering electricity varies at different times of the day in each power system node.

Modeling residential appliance usage is a complex task. This is because it involves technical, economic as well as social issues. Economic factors will affect the consumer's equipment and define how much they can spend on energy bills. Social factors will determine the attitude toward saving electricity.

The purpose of this article is to present the application of the fuzzy-ruled Bayesian algorithm to determine which residential appliances can be considered and at what time for the DR program. The author intends to highlight the key features of this approach and to point out that it can be easily further researched in the field of residential power consumers' reactions to demand response mechanisms. Residential consumers' behavior concerning appliance usage is complex by nature and very often can be described by both randomness and fuzziness. Randomness describes the uncertainty of event occurrence, while fuzziness can measure the degree to which an event occurs but not whether it occurs. Thus, both methods have the potential to be used in the described field.

This paper is organized as follows. Section 2 presents the related research. Section 3 focuses on a detailed overview of materials and methods used for the research. Section 4 describes the obtained results, while Section 5 deals with the performance tests. Section 6 contains a discussion of the results. Finally, Section 7 draws the main conclusions and summaries this study.

2. RELATED WORK REVIEW

2.1. Introduction

This section reviews the previous work relating to the paper topic and outlines the gaps that can be addressed in the present studies. The demand response issue is still relevant. This is evidenced by the published recently large number of scientific articles that deal with this subject. Due to the complexity of this issue, the related work review was divided into three sections focusing on the discussion of papers dealing with demand response, the behavior of residential energy consumers, uncertainty, and fuzzy and Bayesian inference systems.

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2.2. Demand response

The paper [2] focuses on classifying and modeling the demand response in large-scale models with mixed-integer programming. The article [3] presents an incentive strategy of shiftable load participation in DR based on user preferences along with the suggestions for load aggregator (LA). The article [4] proposes also a deep reinforcement learning algorithm for residential DR strategic bidding. The work [5] was devoted to promoting participation in DR programs in Germany while keeping the role of rational and moral motivations. The authors of [6] developed the microeconomic model of consumers designed to answer the question of how they will react to electricity price changes. The paper [7] presents the possible reduction in DR program in the Italian residential sector. Sociodemographic factors influencing DSM are presented in [8, 9]. Willingness to participate in DSM was described in the papers [10] (including time-varying prices) and [11, 12] (including renewable and distributed energy sources)

2.3. The behavior of residential energy consumers

The authors of [13] were analyzing consumer behavior in the case of television energy use. The paper [14] was devoted to modeling residential occupant behavior using sociodemographic predictors. Incentive-based policies in DR like reward and punishment were analyzed in [15]. The authors of [16] described data-driven modeling of energy DR behavior. The work [17] deals with big data analytics in electricity consumers' behavior. The paper [18] highlighted the fact that residential load shifting can be enlarged by consumer behavioral change. The authors of [19] included residential consumer behavior for real-time DR modeling in Smart Grid with renewable energy.

2.4. Uncertainty

Many papers have been also related to the uncertainty in the use of electricity by residential consumers. For example, the authors of [20] propose the simulation of the dynamics of household energy-related activities and appliance usage with a multiagent system model. The papers [21–23] are devoted to the issues of household appliance scheduling while keeping the end user's comfort and satisfaction. The article [24] deals with the operation of the demand response in LA taking into account the uncertainty problems. The work [25] deals with uncertainty in demand response by using the interval method.

2.5. Fuzzy and Bayesian inference systems

Recently, fuzzy logic and the Bayesian approach have been used in the fields such as risk analysis [26], diagnosing [27, 28], reducing electricity consumption [29], or DR management considering incomplete information [30]. Moreover, fuzzy intelligence can be also applied to DR scheduling considering load behavior [31].

2.6. Summary of the review

Numerous approaches were developed and used in previous studies for demand response and residential power consumer appliance usage modeling. However, the above-mentioned methods are not perfect in their applications. This paper attempts to fill in the study gaps by meeting the research objective to develop a suitable and easy-to-use model for further development. This research was motivated by the desire to overcome the weakness of the mentioned approaches, including the inability to take into account the large randomness of household appliance status and recent power system conditions.

The novelty of this paper is the use of the fuzzy-ruled Bayesian inference system to determine which appliances at what time can be considered for the demand response program.

The main contributions of this paper are:

- Dorner's mental model for desires was applied to describe the state of household appliances.
- Power system conditions, represented by nodal prices, are taken into account while modeling DR.
- Fuzzy-ruled Bayesian inference was applied to solve the problem to determine which appliances at what time can be considered for the DR program.
- The modeling process included both fuzziness and uncertainty of residential consumer behavior concerning the usage of appliances.

3. MATERIALS AND METHODS

3.1. Introduction

For research purposes, it was assumed that there are some residential power consumers ready to act according to the DR mechanism. Each of them has different household appliances. This differentiation is manifested not only by having different models of the same device (for example – different manufacturers), but also by using usually divergent operating modes (for example – normal or economical mode). Additionally, consumers are focused on using their appliances when the value of the nodal price is not too high. The situations where their loads require absolute use or re-use may only be an exception.

3.2. The proposed model overview

The research assumed that the possible start of a selected residential appliance can take place by considering:

- The current state of the appliance
- The typical operating time of the appliance
- The current value of the nodal price
- The time of the day

The following assumptions were made during the preparation of the model: (1) a residential consumer can monitor nodal price values on an ongoing basis, (2) only selected appliances (like washing machines or dishwashers), which consumers turn on deliberately, are subject to use at other times than usual, appliances with cycle mode of work are not considered, (3) the simulated data was used since it would be difficult to obtain the real-world data sets, (4) the physical properties of the shiftable appliances were taken into account using the "state of appliance" parameter (this issue was also raised in the paper [2]), (5) it is theoretically possible to collect data on preferences in the use of selected appliances and, on this basis, create the training data set for the reasoning system.

The motivation to adopt the above-mentioned assumptions was the desire to use the information about residential consumers and the power system in terms of the possibility of starting selected appliances. It needs to be emphasized that among all residential consumers, there will be large randomness in terms of the state of their appliances and the preferred time of using them. For this reason, it was decided to apply the fuzzy rule-based Bayesian inference system along with the simulated data sets.

Comparing the assumptions between the presented model and the models from the related work review, several points can be made. In the presented model: (1) the data about willingness to use selected appliances comes from the simulation, while in [8] from surveys, (2) the user turns on selected the appliance purposely when it is necessary, not as in [11] only to maximize the profits, (3) at the beginning of the simulation, the willingness to use the appliance (and indirectly to consider it for DR) is random, while in [11] it is maximum, (4) the use of "state of appliance" parameter corresponds to the consideration of the physical characteristic of the shiftable load, such as "saturation" mentioned in [2], (5) randomness and fuzziness are taken into account, while in [4] only random scenarios and extreme cases are discussed.

The training data consisted of four input variables and one output variable. The following variables were used as the input data: the state of a household appliance, the typical time of appliance operation, the current nodal price value, and the time of the day. The expected value of the willingness to use a given appliance was the output. The high rate of this parameter may be interpreted as a potential consideration of the appliance in the DR program at a given time.

The state of household appliances was modeled using the water tank approach proposed by Dorner [32]. According to this concept, every desire resembles a leaking water tank. If the tank is full, it means that there is no need to satisfy this thirst (or it is not so important) at the moment. However, if the level of water is getting lower for some time, it favors more and more determination to meet the person's needs. In the presented study, the values of the tank level were ranged from 0 to 1. The values close to 0 mean that residential consumer has strong readiness to use a selected appliance (for example to run a washing machine). The values close to 1 mean that there is not enough need to use a given appliance at the present moment or there is a low probability to run it again.

The typical time of appliance operation was set from 20 to 120 minutes. This is the representative operating time range for most household appliances. The current nodal price values were set from 40 to 48 \$/MWh. The value of the nodal price reflects the present operating conditions of the power system such as generation cost, active power load, transmission power losses, and congestion of branches. The time of day was narrowed to the range between 5 a.m. and 9 p.m. During this period, residential consumers can run their appliances in the morning (before going to work) as well as in the afternoon or evening.

The expected value of the willingness to use the given appliance was set to range between 0 and 1. This value is the result of the simultaneous occurrence of each of the four input values and corresponds to the final decision on the possible activation of the given household appliance.

3.3. Training data

The values representing the willingness to use household appliances were generated using the model made in Matlab/Simulink with Fuzzy Logic Toolbox [33] (Fig. 1). The model consisted of 4 inputs and 1 output. The inputs were: the state of the household appliance, the typical appliance operating time, LMP price values, and the time of the day. The output was the willingness to use ranging from 0 to 1. The main part of the presented model was the fuzzy inference system (FIS) consisting of a fuzzification interface, a database, a rule base, a decision-making unit, and a defuzzification interface. The crisp input predictors were converted into fuzzy numbers by the fuzzification interface. The membership functions were stored in a database, while fuzzy rules are in the rule base. All rules were in IF ⟨antecedent⟩ – THEN ⟨consequent⟩ configuration.

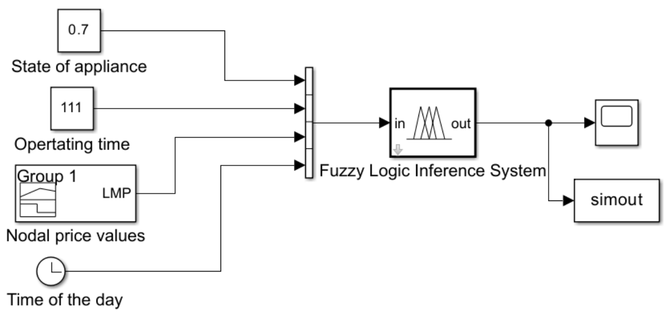

Fig. 1. Matlab/Simulink model used to generate training dataset. Own work, based on [33]

The decision-making unit performs the inference processes using fuzzy rules. Lastly, the fuzzy inference results are converted to the crisp output values by the defuzzification interface. Finally, the training set consisted of 5 data columns. The first four columns were input data from the FIS and the fifth column contained the corresponding output value.

After the creation of the training data set, the configuration of the fuzzy-ruled Bayesian inference system was performed. To use this method, four new membership functions were created (Figs. 2–5). Each of these functions corresponded to one of the

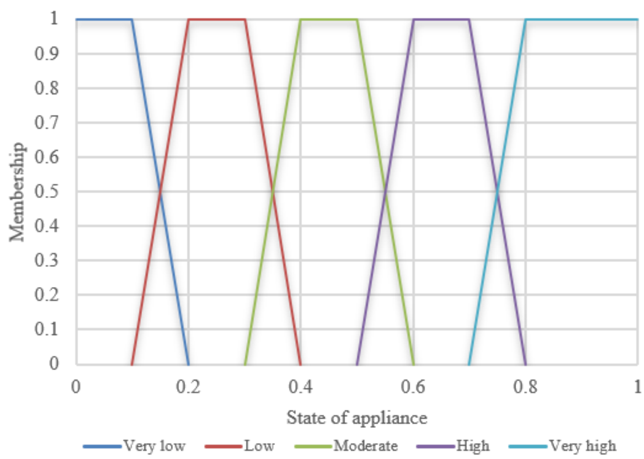

Fig. 2. Membership functions for the state of the appliance. Own work

input values in the training data set. All membership functions were of the trapezoidal type. Their shapes were sufficient for the examined decision problem. The colors indicate membership functions.

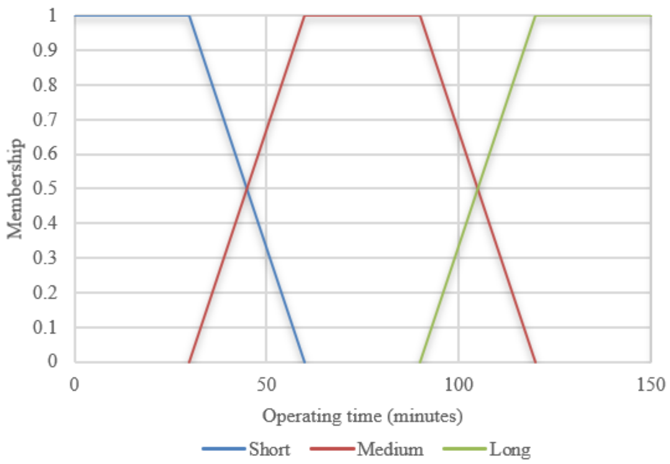

Fig. 3. Membership functions for operating time. Own work

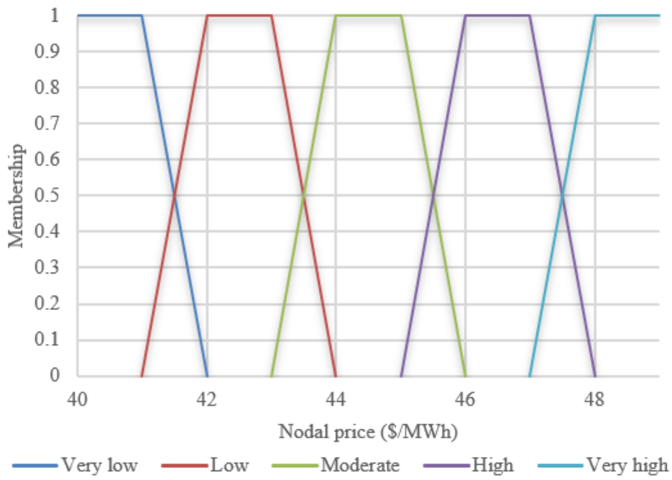

Fig. 4. Membership functions for the nodal price. Own work

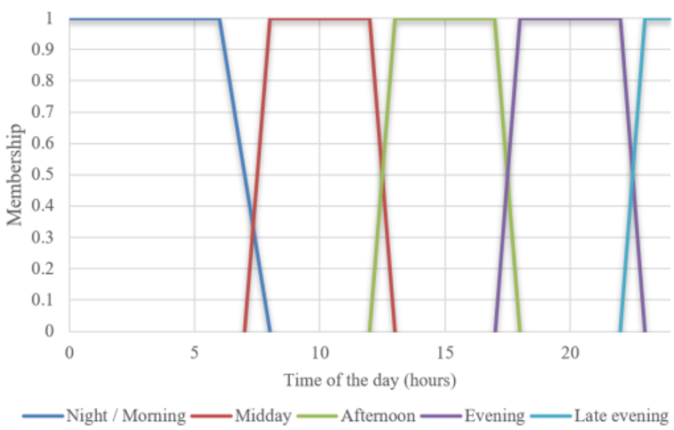

Fig. 5. Membership functions for the time of the day. Own work

3.4. Research methodology

The research presented in this paper consisted of:

- Creating the simulated set of training data – four predictor variables were used: the state of the household appliance, the typical time of an appliance operation, the nodal price value, and the time of a day. Each group of these four data was assigned one response variable – willingness to use. The whole training set consisted of 100 groups of the 5 above-mentioned variables (4 inputs and 1 output).
- Creating the simulated set of testing data – the same kind of four predictor variables, as in the training data set, were used but they all had different random values. The range of randomly generated values was dedicated to each predictor variable, for example in the case of the state of appliances it was between 0–1, and in the case of the nodal prices it was between 40–48 $/MWh. The whole testing set consisted of 200 groups of the 5 variables (4 inputs and 1 hidden output).
- Predicting the value of the response variable (willingness to use) for each predictor combination from the simulated testing data set. The output was the crisp value ranging from 0 to 1.

3.5. Fuzzy-ruled Bayesian inference

The input data for Bayesian inference are usually different states which can be undertaken by the studied system. These states constitute the set S [34], given by equation (1):

$$S = \{S_1, S_2, \ldots, S_n\}. \tag{1}$$

Each possible user's decision is a specific action a_{i-th} contained in set A (set of actions), given by equation (2). All actions are considered alternatives:

$$A = \{a_1, a_2, \ldots, a_n\}. \tag{2}$$

Likewise, the output data can also be interpreted directly as system parameters. By combing fuzzy logic with Bayesian inference, it enables the study of the phenomena that characterize ambiguity and uncertainty. HABFUZZ [35] software was used for performing the fuzzy-ruled Bayesian inference. In general, this algorithm can be described in three steps:

Step 1: The process of the input variables fuzzification – the process begins with defining a membership function for each input (a predictor) variable (Figs. 2–5). Next, each input value is assigned to at least one fuzzy set. As a result, all crisp values are changed to fuzzy values described by membership degree for every fuzzy set. All degrees are ranged from 0 to 1. Every IF–THEN rule was learned automatically by the program according to the simulated training data set.

Step 2: Bayesian joint probability calculation process – it is assumed that all four input predictors are independent of each other (for example, the nodal price at a given time is independent of the state of the appliance). Equation (3) is used to calculate the joint probability of independent actions (possible decisions made by the user):

$$P(A \cap B) = P(A\,|\,B) * P(B) = P(B\,|\,A) * P(A), \tag{3}$$

where: $P(A \cap B)$ – the probability of action A and action B occurring together, $P(A \mid B)$ – the conditional probability of action A occurring that action B occurred earlier, $P(B \mid A)$ – the conditional probability of action B occurring that action A occurred earlier.

In the presented study it was assumed that $P(A \mid B) = P(A)$, hence equation (3) becomes equation (4):

$$P(A \cap B) = P(A) * P(B). \tag{4}$$

The probabilities of occurring states of nature are called prior probabilities. These probabilities are updated with the usage of observations from the vector $\mathbf{X} = \{x_1, \ldots, x_n\}$ regarding states S. This information is expressed using the handling of conditional probabilities also called likelihood values. The likelihood values are used as weights to the prior probabilities to find the updated probabilities called posterior probabilities.

Step 3: The classification of the response (output) variables – is performed by using equation (5):

$$\mathrm{EU}(A) = \sum_{i=1}^{n} P(x_i \mid A) * U(x_i), \tag{5}$$

where: $\mathrm{EU}(A)$ – the value of expected utility of action A, x_i – i-th element of the observation vector $\mathbf{X}$, $P(x_i \mid A)$ – the probability of x_i conditioned on action A, $U(x_i)$ – a utility weight used for converting the state to the numerical value.

In the presented study the values of the EU were used to describe the willingness to use the appliance. The score was:

- $U = 0.1$ – there is very little chance that the appliance will run under given conditions,
- $U = 0.3$ – there is a little chance that the appliance will run under given conditions,
- $U = 0.5$ – there is a moderate chance that the appliance will run under given conditions,
- $U = 0.7$ – there is a high chance that the appliance will run under given conditions,
- $U = 0.9$ – there is a very high chance that the appliance will run under given conditions.

The concept of expected utility comes from economics. The utility function is used for measuring consumers' preferences for a set of services or goods. Economists can use it to understand consumer behaviors more deeply. Moreover, they can be able to determine how well some services or goods will fulfill consumers' expectations.

Every fuzzified membership degree is treated as the probability of each observation. The final output value came from multiplying the probability by its score and summing it up. Further and detailed information about the fuzzy Bayesian decision method can be found in [34, 36].

Figure 6 presents the three-dimensional representation of the used 100 training data set samples (a ready set that contained all the data used to train the system). The current time is placed on the X-axis, while the operating time of a given appliance is on the Y-axis. The Z-axis shows the willingness to use a given appliance. Additionally, these values were marked with different colors. A darker color means little willingness to use, while lighter colors mean – greater willingness.

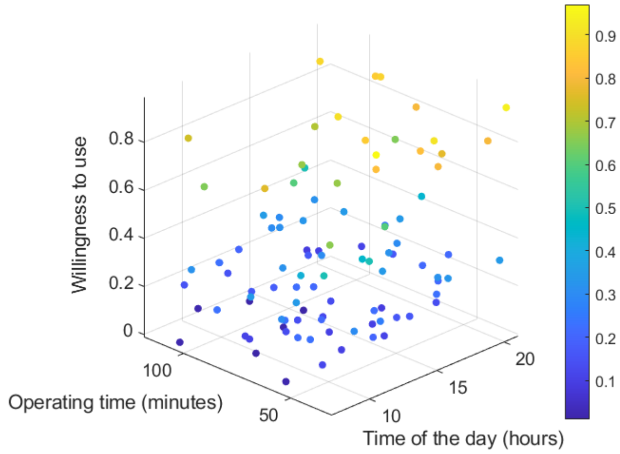

Fig. 6. Three-dimensional representation of simulated training dataset. Own work

4. RESULTS

The set of 200 samples (simulated testing set) for the presented case study was used for research purposes.

Due to the complexity of the obtained data, they were presented by 3D control surfaces. Each of them illustrates three variables: the willingness to use and two selected predictors.

Figure 7 presents the first 3D control surface plot of the fuzzy system. The nodal price values are placed on the X-axis, while the state of appliances values are on the Y-axis. The Z-axis shows the willingness to use a given appliance under the specified conditions. The figure shows that the greatest willingness to use applies to the cases when the state of the appliance is small (around 0.2) even if the value of the nodal price can be medium or high (from 44 to 48 \$/MWh).

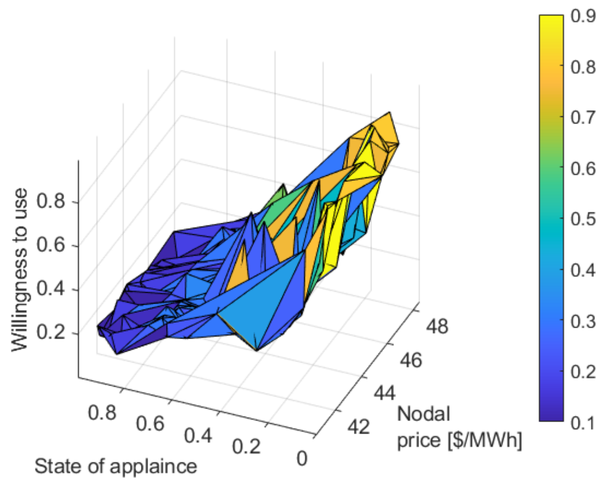

Fig. 7. Control surface plot. Own work

Figure 8 presents the second 3D control surface plot of the fuzzy system. The operating time values are placed on the X-axis, while the state of a given appliance is on the Y-axis. The Z-axis shows the willingness to use a given appliance under the specified conditions. The figure shows that the greatest willingness to use applies to the cases when the state of an appliance is low or close to medium, along with the operating time of around 60–80 minutes.

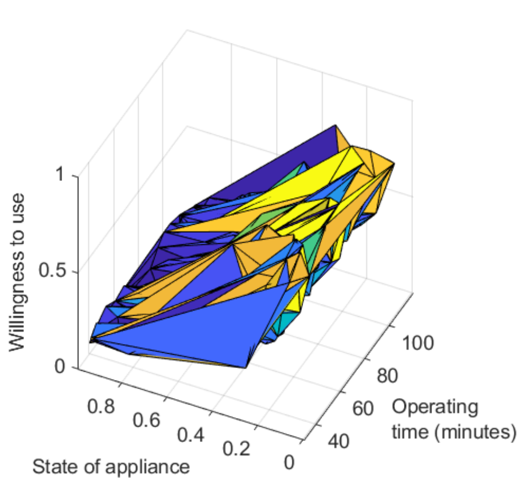

Fig. 8. Control surface plot. Own work

Figure 9 presents the third 3D control surface plot of the fuzzy system. The operating time values are placed on the X-axis, while the time of the day is on the Y-axis. The Z-axis shows the willingness to use a given appliance under the specified conditions. The figure shows that the greatest willingness to use applies to cases when the time of day is around 15:00 (3 P.M.) and around 20:00 (8 P.M.). The obtained values of the willingness to use a given appliance indicate that the residential consumer would most likely turn on the given appliances immediately after returning home from work (when the nodal price has not increased yet) or during the afternoon/evening peak begins around 20:00 (8 P.M.) and the nodal prices may decrease.

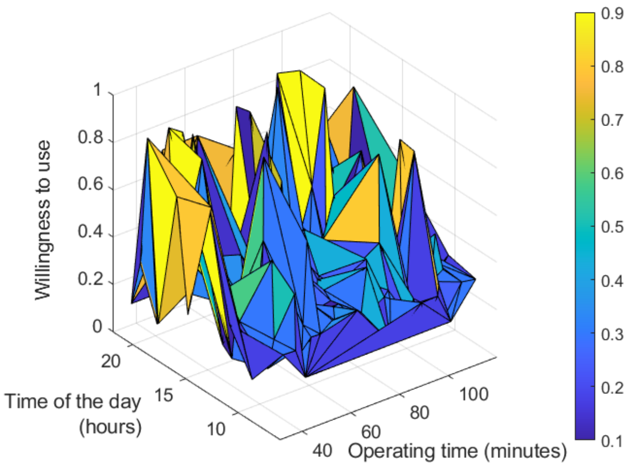

Fig. 9. Control surface plot. Own work

5. PERFORMANCE TESTS

To check the performance of the proposed model, the R^2 coefficient and root mean square error (RMSE) calculations were applied. R^2 is also called the coefficient of determination and is very often used as the measure of how well the obtained results (outputs) are replicated by the model. Its value can be in the range from 0 to 1, where a greater rate means better fitness. The value of R^2 can be calculated from equation (6):

$$R^2 = 1 - \frac{\text{SSE}}{\text{SST}} = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2}, \tag{6}$$

where: SSE – the sum of squared errors, SST – the sum of squared total (difference between the observed dependent value and its mean), y_i – i-th actual value of the dependent variable, $\hat{y}_i$ – i-th model predicted value of the dependent variable, $\bar{y}_i$ – the mean statistic of the dependent variable.

The RMSE value was calculated using equation (7). The lower the error value, the better the quality of the model:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}, \tag{7}$$

where: n – the number of prediction points, y_i – the actual value, $\hat{y}_i$ – the predicted value

Table 1 shows the results of performance tests of the proposed model using R^2 and RMSE values. Figure 10 shows R^2 of outputs from the test dataset and the HABFUZZ. Figure 11 shows the comparison of two outputs but in the form of a line graph. The outputs from the test dataset are marked in blue, while the outputs from the HABFUZZ program are marked in orange.

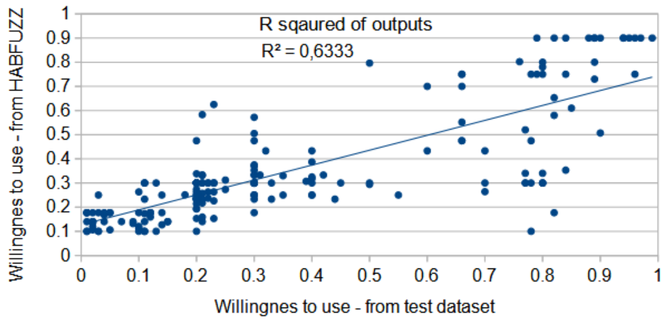

Fig. 10. R squared of outputs. Own work

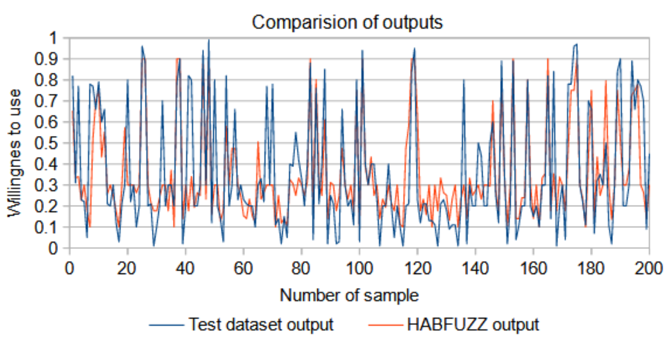

Fig. 11. Comparison of outputs. Own work

Table 1
Results of performance tests

Dataset type	Measure	
	R^2	RMSE
Training	0.7438	0.6092
Testing	0.6333	0.6151

6. DISCUSSION

From the analysis of the results presented in Figs. 7–9 and performance tests, it can be concluded that the fuzzy rule-based Bayesian inference algorithm discovered the regularities contained in the training data set well. Adjusting the value of the willingness to use a given household appliance under the influence of four predictor values based on the test data set was performed in accordance with the expectations resulting from the regularities included in the training data.

The fuzzy rules learned by the presented algorithm are rich enough to cover a big variety of household appliance usage.

It should be emphasized that the results obtained from this type of inference do not necessarily mean only the optimal ones. Very often their values constitute a sufficiently good choice in the current decision-making circumstances. This is also facilitated by the use of the expected utility (equation (5) [36].

The obtained values of the verification measures (R^2 and RMSE) allow to conclude that the quality of inference is satisfactory. Moreover, the RMSE value for the training dataset is slightly lower than for the testing dataset, which confirms that the model is not much prone to overfitting.

The advantage of using the presented approach is the ease of preparing the training data set. The nodal price values can be derived from the network models used to calculate the AC optimal power flow (OPF). The total computation time of the test data is quite short. Compared to other mentioned approaches, this method overcomes the problem of lack of the randomness in state of appliances and lack of reference to the recent power system conditions. Moreover, the presented solution includes learning and adaptation, since the process of electricity usage may be highly dynamic in some cases.

However, the difficulty in the graphical presentation of the results is the disadvantage of the used method. The use of colored 3D control surfaces can lead to reduced legibility when the test data set is large. The usage of only trapezoidal or triangular fuzzy membership functions is another potential limitation of this method. The Gaussian function cannot be used here. The quality of the results will depend to a large extent on how well the inference rules are defined.

7. CONCLUSIONS

The objective of this paper was to present the application of the fuzzy rule-based Bayesian algorithm to determine which residential appliances at what time can be considered for the demand response program. The presented research confirmed the usefulness of fuzzy rule-based Bayesian inference for modeling this type of phenomenon.

The proposed method assumes that it is possible to determine with the use of 4 input data whether the consumer would be willing to turn on purposely the selected appliance, hence it can be potentially considered for the DR program. The presented model also includes the physical characteristics of shiftable loads. In many DR models these aspects are ignored or overlooked [2]. Compared to models from the related work review, the introduced solution takes into account the high randomness and fuzziness during the use of household appliances. In addition, the value of the nodal price was also considered.

If the registration of each start-up of a given appliance and the accompanying external conditions (like operating time, and nodal price) were introduced, a database could be created on the preferences of each user. Based on the data from these measurements, the inference system could learn according to which rules everyone uses electricity and, as a result, predict these behaviors in the future. Under the terms of Bayesian inference, the more data, the better it can be determined whether the initial hypothesis can be considered more or less certain.

Over the years, fuzzy logic has proven its usefulness in making decisions based on uncertain input data. Together with the set of real measurement data, a system based on the presented concept could be implemented in practice.

Machine learning and forecasting methods require a large amount of training data, which collecting can be expensive or time-consuming [37]. The presented solution can work with a smaller amount of data and at the same time give satisfactory results. If more data is acquired in the future, the current model may be updated easily.

The fuzzy rule-based Bayesian inference algorithm can successfully complement the traditional fuzzy logic tools. In addition, its use allows for shortening the research time because there is no need to create the extensive IF-THEN rule base or perform a long rule base training process. One can build the training data set from the basic fuzzy inference system and get the results for the bigger test data set by applying Bayesian inference. The proposed approach can be easily used by the power network managers to obtain more objective and flexible information about possible DR capacity. Such an action may become more important with the growing energy crisis. The presented solution provides a satisfactory representation of the uncertainty of household appliance usage. Moreover, the output data can be directly interpreted. The results from the presented system can be used as a supplement or extension of other techniques, for example, consumer clustering or machine learning for DR.

The possible paths for future research in this field may be the application of different kinds of membership functions, combing the presented solution with another inference technique by creating a new hybrid method, the use of the presented results to support the methods of forecasting energy consumption or creating new scheduling scenarios including individual user preferences.

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