Forecasting of Residential Power Consumer Load Profiles Using a Type-2 Fuzzy Inference System

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Abstract: The key focus of this article is forecasting of residential power consumer load profiles using tuned Type-2 Fuzzy Inference System. The characteristics of residential load profiles have been investigated. In contrast to similar studies, non-averaged profiles with one minute resolution have been used. Additionally, the presence of various shapes in these profiles increases the difficulty of forecasting. In this paper, the process of creating, learning and tuning Type-2 Fuzzy Inference System with Particle Swarm Optimization and Genetic Algorithm is presented. The accuracy of the forecasts was evaluated using Root-Mean-Square Error calculations. The obtained results showed that the proposed method can predict detailed load profiles efficiently. The biggest forecast error was 0.1165, while the lowest was 0.0642. Additionally, the value of error was influenced also by the type of day (working day or Saturday). Moreover, the Particle Swarm Optimization proved to be a more precise tuning solution than the Genetic Algorithm, obtaining lower error values. Several aspects related to the residential load profiles forecasting are also discussed in this paper. The presented research may be useful for companies selling electricity.

Keywords: load profiles; residential power consumers; forecasting; fuzzy logic; type-2 fuzzy inference system

1 Introduction

The issues of forecasting the power demand of electricity consumers are still an important challenge. This is due to several key factors such as: variability in the way electricity is used, new forecasting methods and changes in power sector like increasing number of renewable energy sources and electric vehicles. In the power system, the generated power must be balanced by the received power. Hence, it is particularly important to know the power demand of end users. Power consumers can be categorised into three groups, namely: industrial, service and residential loads.

According to [6], residential power consumers constitute around 30% of the electricity usage. This relationship remains at a similar level in many European countries. Additionally, energy usage increases from year to year. Electricity consumption as a function of time is presented by load profiles. These profiles can be observed daily, monthly or annually. Each power consumption results in the formation of an appropriate shape in the profile course. Moreover, even devices of the same type but from different manufactures or in dissimilar working mode may cause completely different shapes. Averaged profiles are very often used for further research and decision making. However, averaging causes significant changes to the shape of the original profile – flattening and smoothing of the basic shapes are created. Hence, it is desirable to use full, non-averaged load profiles.

Forecasting electricity consumption is still an important and current issue. For example, the paper [16] reviews the modern electric load forecasting technologies, while the article [22] presents household load forecasting using the Gradient Boosted Regression Tree combined with Sequence-to-Sequence Long short-term memory networks. In [7], Deep Learning and K-means Clustering was used for short-term residential load forecasting. Load profiles can also be treated as seasonal time series with some trends. Authors of paper [3] was indicating how important is to forecast time series in Tourism.

Fuzzy Logic is applicable too many problems such as: sound quality prediction [15], cardiovascular diseases identification [24], clustering [4] [27] or tower crane modeling [8]. Moreover, fuzzy logic is also still developing – for example, authors of paper [13] propose new fuzzy modus ponens and modus tollens for approximate inference with uncertainty. Paper [2] deals with decision-making and control in medical applications which can be also combined with fuzzy logic. Type-2 Fuzzy Logic is an extended version of the Type-1 Fuzzy Logic [9] and can be applied in the power engineering to such issues as: power system stability [10], automatic generation control [18] or power quality [21].

In recent years numerous problems in load forecasting have been examined and solved using fuzzy logic. In [20], very short-term (10 seconds) forecasting of power demand of highly variable loads in microgrids was presented. One of the methods used for this type of research was tuned Type-2 Fuzzy Inference System (T2FIS). This article highlights the relatively long computation time when tuning fuzzy system. The paper [9], proposes the hybrid fuzzy load forecast method with the modified Jaya optimization algorithm. Load forecasting results of the evaluated system turned out to be better than similar hybrid Ant Colony-Fuzzy solution. In [17], the hybrid system of Weighted Least Squares State Estimation, Neural Network and Adaptive Neuro-Fuzzy Inference System was presented. The combination of the three above-mentioned system gave very good forecasting results with a low Mean Absolute Percentage Error (MAPE). The authors of [5] propose to divide the problem of load forecasting into smaller subproblems. Each subproblem is solved separately using Takagi-Sugeno fuzzy model. More accurate solutions of subproblems results in a better quality of the forecast. In the paper [1], fuzzy logic was used to create load profiles taking into account individual characteristics of a given power consumer. The article [25] concerns forecasting day-ahead hourly energy consumption profile of a residential building including occupancy rate. The paper [23] draws attention to the use of air temperature as a variable in the process of forecasting electrical loads using Adaptive Neuro-Fuzzy Inference System.

The importance of the presented issue is evidenced by a large number of the research work in this filed. In the analyzed related papers, different time series and forecasts methods were considered. However, above-mentioned articles do not deals simultaneously with forecasting full (non-averaged) and dense (1-minute resolution) residential load profiles with a tuned Type-2 Fuzzy Inference System. The aim of this article is to perform a presentation of Type-2 FIS usage for high resolution load profiles forecasting as well as selection of the best fuzzy logic learning and tuning process parameters. This paper attempts to fill in the research gaps by meeting the research objective to develop a suitable and easy to use model for further time series forecasting studies. This research was motivated by the desire to overcome the shortcomings of the mentioned approaches, including the inability to take into account wide-range various shapes caused by household appliances which can lead to difficulties in forecasting processes.

In this article the application of tuned Type-2 Fuzzy Inference System for residential power consumer load profiles forecasting has been investigated. The proposed approach can be used to predict dense load profiles with satisfactory results. This paper is organized as follows: Section 2 describes residential power consumer load profiles. Section 3 presents the Type-2 FIS usage. In Section 4 the results of forecasting (with performance measure) and discussion are introduced. Finally, last part of this article focuses on conclusions.

2 The Characterisics of Residential Power Consumer Load Profiles

The observation of load profiles provides a lot of information about the way in which the consumer uses electricity. The load profiles are most often in the form of the variation of active power as a function of time. The variability of active energy appears less frequently. The main factors influencing the power demand of household consumers are: equipment with electricity receivers (usually - the larger the size of the house, the greater power consumption), time of using electricity and a consumer attitude. Regardless of details about the consumer, certain repetitive patterns can be observed in each load profile – these are base load with morning and evening peaks. The base load is mainly due to the devices in a stand-by mode and operation of refrigerators, while morning or evening peaks are caused by devices that are turned on temporarily.

Load profiles for each consumer differ between working days and non-working days. Typically on working days, the morning peak occurs before the residents leave for work. There are no major changes in power consumption while they are away from home. After coming from work, various receivers are turned on and evening peak is present. It lasts longer than the morning peak and ends before the midnight. During the weekend (Saturday and Sunday), the morning peak starts later and also temporary peaks occur at noon.

For the purpose of this study, load profiles from two different households were used. Both examined flats were equipped with different electricity receivers. In addition, there were also differences in the amount of consumed power. Household 1 was occupied by three people, while household 2 only by two.

Figure 1 presents household 1 load profile measured during a typical working day in winter. Figure 2 presents also household 1 in winter, but on Saturday.

Figure 3 presents household 2 load profile measured during a typical working day in winter. Figure 4 presents also household 2 in winter, but on Saturday.

All mentioned load profiles have a one-minute resolution. Furthermore, the active power values have been normalized to unity. Due to the lack of averaging, the characteristic shapes of power consumption have been maintained in each household.

In recent years, there has been a growing interest in the use of Smart Grids and Smart Meters. Increasing metering of the low voltage network will result in the appearance of big data. A large part of this data will concern residential load profiles. So, the detailed profiles may prove useful in planning the development of the network or matching the tariffs of the energy supplier to the consumer.

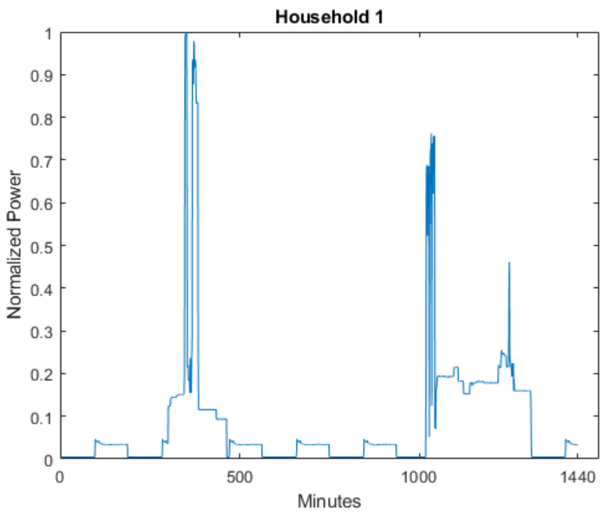

Figure 1
Household 1 load profile, winter, working day. Own work, based on [11]

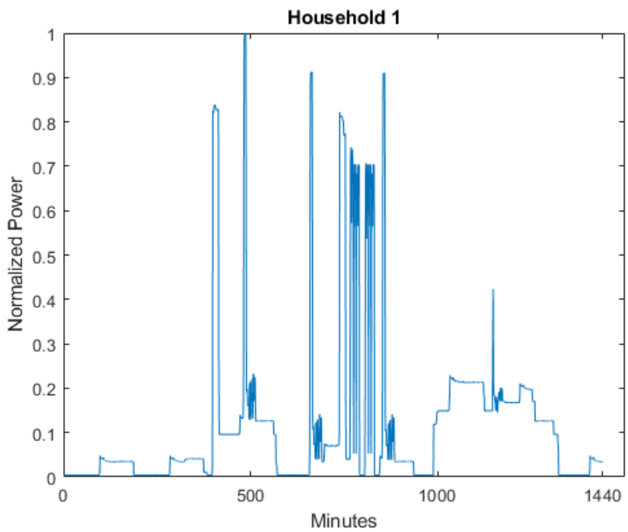

Figure 2
Household 1 load profile, winter, Saturday. Own work, based on [11]

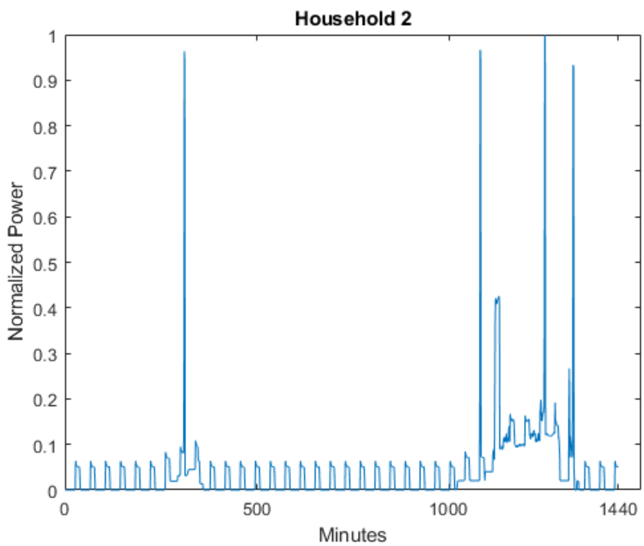

Figure 3
Household 2 load profile, winter, working day. Own work, based on [11]

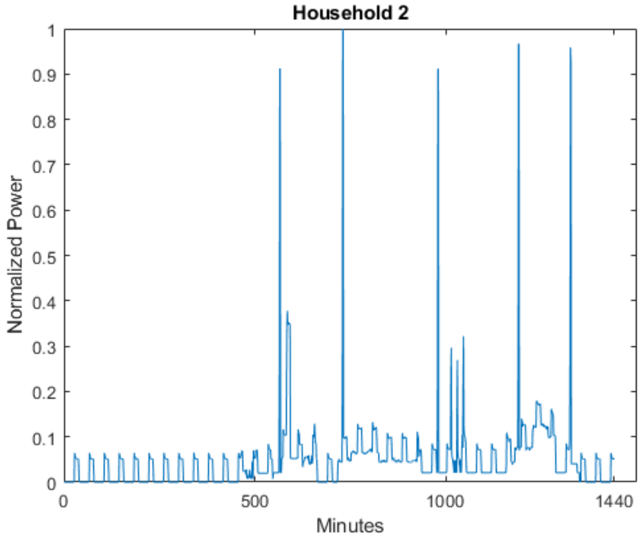

Figure 4
Household 2 load profile, winter, Saturday. Own work, based on [11]

3 Forecasting Residential Power Consumer Load Profiles with Tuned Type-2 Fuzzy Inference System

3.1 Introduction to Type-2 Fuzzy Inference Systems

Fuzzy logic (FL) was proposed by Lotfi A. Zadeh in 1965. Unlike traditional logic, there are intermediate values between zero and one in fuzzy logic. These values have a specific membership function (MF) values to a given set. The purpose of the development of the fuzzy sets (FS) theory was to describe the phenomena of a non-precise and ambiguous nature. Numerous applications prove the importance of fuzzy logic in technology.

A Fuzzy Inference System (FIS) is a system that based on sets of rules interprets the values in the input data set, to the output data. The rule can be written as (1):

$$R^n : IF\ x_1\ IS\ X_1^n\ and \dots x_p\ IS\ X_p^n,\ THEN\ y(x) = c_0^n + c_1^n \cdot x_1 + \dots + c_p^n \cdot x_p \tag{1}$$

where: R^n - rule, p - numer of inputs, $y(x)$ - output function, $\{c_k^n\}_{k=0,\dots,p}$ - crisp coefficients.

The fuzzy inference process can be divided into three parts: fuzzification, rule evaluation and defuzzification. Fuzzification is a process in which crisp input values are evaluated how they belong to defined fuzzy sets by using membership functions. Rule evaluation computes output fuzzy values and determines how the rules can be activated and combined. Defuzziifcation provides a crisp output value, which is a precise information for further control or decision making.

In 1975 Zadeh introduced Type-2 fuzzy sets. They are an extension of the previous fuzzy sets (referred to as Type-1). A Type-2 FS $\overset{\approx}{A}$ can be represented by formula (2) [14].

$$\overset{\approx}{A} = \{(x,u), \mu_{\overset{\approx}{A}}(x,u) \mid \forall x \in X, 0 \le \mu_{\overset{\approx}{A}}(x,u) \le 1\} \tag{2}$$

where: $\forall u \in J_X \subseteq [0,1]$.

Contrary to Type-1 FS, Type-2 sets have three-dimensional membership functions with footprint of uncertainty (FOU). FOU (3) is describing the union of all memberships. The lower and upper bounds of FOU are Type-1 MFs, called Lower Membership Function (LMF) (4) and Upper Membership Function (UMF) (5).

$$FOU(\overset{\approx}{A}) = \bigcup_{x \in X} J_X = \{(x,u) : u \in J_X \subseteq [0,1]\} \tag{3}$$

$$\bar{\mu}_{\overset{\approx}{A}}(x) = \overline{FOU(\overset{\approx}{A})}, \forall x \in X \tag{4}$$

$$\mu_{\overset{\approx}{A}}(x) = \underline{FOU(\overset{\approx}{A})}, \forall x \in X \tag{5}$$

The advantage of using Type-2 fuzzy logic is the possibility of modeling uncertainty in the degree of membership. Thanks to this approach drawback of uncertainty in the rule base can be minimized [12]. Interval membership functions can be used here. An example of such a function is shown in Figure 5. The area dA of the region between the LMF and UMF can be found by formula (6).

$$dA = (\bar{\mu}_{\overset{\approx}{A}}(y) - \mu_{\overset{\approx}{A}}(y)) \cdot dy \tag{6}$$

Additionally Type-2 inference systems contain a reducing block, which is used before the final defuzzing process. Figure 6 presents a schematic diagram of the Type-2 FIS. The final crisp value of y is determined by the equation (7).

$$y_{Crisp} = \frac{\int_{-\infty}^{\infty} y \cdot dA}{\int_{-\infty}^{\infty} dA} == \frac{\int_{-\infty}^{\infty} y \cdot (\bar{\mu}_{\overset{\approx}{A}}(y) - \mu_{\overset{\approx}{A}}(y)) \cdot dy}{\int_{-\infty}^{\infty} (\bar{\mu}_{\overset{\approx}{A}}(y) - \mu_{\overset{\approx}{A}}(y)) \cdot dy} \tag{7}$$

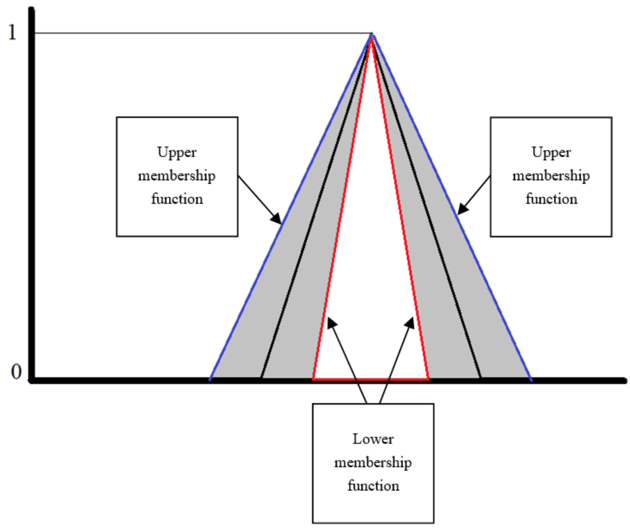

Figure 5
Example of interval membership function. Own work, based on [29]

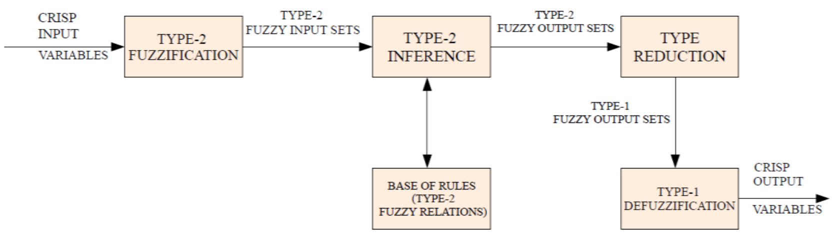

Figure 6
The idea scheme of Type-2 Fuzzy Inference System. Own work, based on [20]

The modeling steps of FIS for forecasting time series can be described as follows: 1) Prepare time series (with data normalization), 2) Prepare training and validation data sets from the examined time series, 3) Construct FIS (Type-1) with default parameters, 4) Learn the rule base with constant MF parameters (using one selected method, for example Particle Swarm Optimization (PSO) or Genetic Algorithm (GA)), 5) Tune the output MF and the upper MF (formula (4)) while keeping the rule and lower MF parameters constant (with PSO or GA), 6) Tune the lower MF (formula (5)) of the inputs while keeping rule, output MF and upper MF constant (with PSO or GA), obtain complete Type-2 FIS and find crisp output values (formula (7)), 7) Evaluate Type-2 FIS performance with RMSE (formula (8)) values, 8) Change some model parameters (type of MF) and optimization method parameters (number of iterations, selected method), 9) Repeat steps 3-7.

3.2 Creating, Learning and Tuning of Type-2 Fuzzy Inference System for Load Profiles Forecasting

3.2.1 Creating a Fuzzy Inference System

The research was carried out in the Matlab environment with the Optimization Toolbox and Fuzzy Logic Toolbox. In each of the examined cases, the Fuzzy Inference System had 3 inputs and 1 output. The same load profile shifted by one minute was used as inputs. Consequently, the values of $x(t+1)$ were predicted from the past values of $x(t)$, $x(t-1)$ and $x(t-2)$. The output was the forecasted load profile. Odd values from the input data set were used as training data, while even values from the input as validation data for FIS.

The Sugeno version was chosen as the type of inference system. Three triangular membership functions were assigned to each of the inputs. The output was with constant MFs. To achieve the best input-output mapping, the maximum possible number of MFs on the output was set to 3^3=27. Figure 7 presents FIS with three inputs and one output.

Initially, footprint of uncertainty for every input membership function was eliminated. Hence, Type-2 FIS was equal to a Type-1.

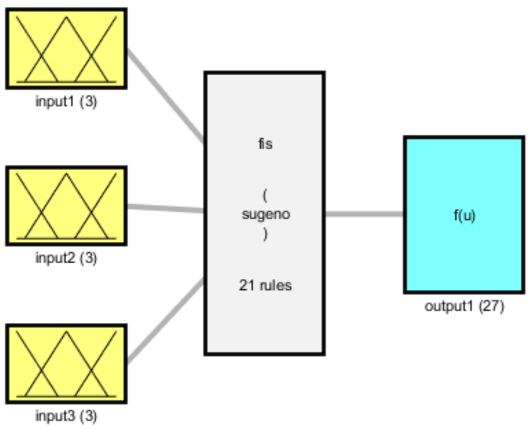

Figure 7
Fuzzy Inference System with three inputs and one output. Own work

3.2.2 Learning a Fuzzy Inference System

Once the FIS was created, the iterative learning process could begin. Structural adaption of the system is the goal of learning [26]. Consequently, the membership function parameters were changed and the base of rules had the smallest possible size. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) were chosen as the learning methods. The number of iterations was set to 10, 15 or 20.

The PSO algorithm was established in 1995 and belongs to a group of stochastic nonlinear optimization methods. Its creating was inspired by its behaviour observed in nature. PSO can solve a problem by using a population of candidate solutions. A particle is each potential solution. Particles are moving around the given space with some velocity and position. The whole swarm is moving toward the best possible result. PSO does not require additional system knowledge and can search large spaces quickly, which is a huge advantage [28].

Genetic Algorithm as a method of optimization was also inspired by nature. It uses operations of selection, mutation and crossing. Each candidate solution (also called phenotypes) has a set of properties (chromosomes) which can be changed - altered or mutated.

Both optimization methods have some common features: space searching is based on a group of individuals (PSO – swarm, GA – population) and initial population is generated randomly.

The learning process concerned a Type-1 FIS. The Type-2 system is obtained after the membership function tuning is completed.

3.2.3 Tuning a Fuzzy Inference System

The FIS tuning process servers to adjust the membership functions parameters. This is especially required when the input data set is large. PSO and GA were again used as optimization methods. The upper and lower parameters of the membership functions were tuned while the base of rules remained constant.

The decreasing Root Mean Square Error (RMSE) was a measure of the improvement in FIS performance after the tuning process was completed. RMSE is given by formula (8). The smaller the error value, the better forecast.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

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

The tuning operations should be carried out carefully. Too big number of iterations can lead to FIS overfitting and an increase in RMSE values on validation data.

Figure 8 presents the complete Type-2 FIS after learning and tuning. The shapes of the triangular membership functions were changed.

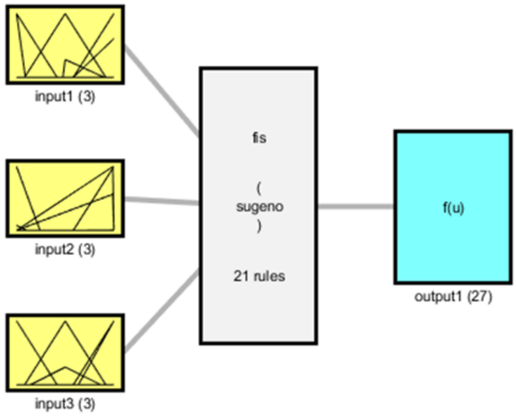

Figure 8
Type-2 Fuzzy Inference System after learning and tuning. Own work

3.2.4 The final Fuzzy Inference System

For the purposes of the presented studies, four different FIS variants were prepared. Table 1 presents the basic parameters of each variant.

Table 1
Basic parameters of Fuzzy Inference Systems

FIS variant	Learning and tuning method	Number of learning and tuning iterations	Type of membership functions
1	PSO	10, 15 or 20	Triangular
2	PSO	10, 15 or 20	Gaussian
3	GA	10, 15 or 20	Triangular
4	GA	10, 15 or 20	Gaussian

As a result, each of the four mentioned load profiles was forecasted by 12 different FIS versions (4 variants with 3 iteration numbers). The measure of the forecast accuracy was the RMSE value obtained for the validation data (720 samples) and the evaluation data (1440 samples).

The other FIS parameters are: AND operator method (Product of fuzzified input), OR operator method (Probablistic), Implication method (Product), Aggregation method (Sum), Defuzzification method (Weighted average of all rule outputs) and Type of Reduction method (Karnik-Mendel).

4 Forecasting Results and Discussion

4.1 Household 1 Results

Table 2 and Table 3 present results for working day and Saturday respectively.

Table 2
Forecasting results of household 1 load profile, winter, working day

Forecast number	Learning and tuning method	Number of learning and tuning iterations	Type of membership functions	RMSE on validation data set	RMSE on evaluation data set
1	PSO	10	Triangular	0.0583	0.0729
2	PSO	15	Triangular	0.0564	0.0661
3	PSO	20	Triangular	0.0490	0.0704
4	PSO	10	Gaussian	0.0564	0.0647
5	PSO	15	Gaussian	0.0539	0.0642
6	PSO	20	Gaussian	0.0559	0.0740
7	GA	10	Triangular	0.0606	0.0727
8	GA	15	Triangular	0.0566	0.0700
9	GA	20	Triangular	0.0571	0.0706
10	GA	10	Gaussian	0.0579	0.0731
11	GA	15	Gaussian	0.0547	0.0750
12	GA	20	Gaussian	0.0571	0.0763

Table 3
Forecasting results of household 1 load profile, winter, Saturday

Forecast number	Learning and tuning method	Number of learning and tuning iterations	Type of membership functions	RMSE on validation data set	RMSE on evaluation data set
1	PSO	10	Triangular	0.0855	0.1057
2	PSO	15	Triangular	0.0853	0.1103
3	PSO	20	Triangular	0.0864	0.1153
4	PSO	10	Gaussian	0.0850	0.0997
5	PSO	15	Gaussian	0.0884	0.1060
6	PSO	20	Gaussian	0.0852	0.1010
7	GA	10	Triangular	0.0907	0.1053
8	GA	15	Triangular	0.0815	0.1073
9	GA	20	Triangular	0.0855	0.1076
10	GA	10	Gaussian	0.0895	0.0949
11	GA	15	Gaussian	0.0885	0.1057
12	GA	20	Gaussian	0.0858	0.1165

4.2 Household 2 Results

Table 4 and Table 5 present forecasting results for household 2 load profiles, working day and Saturday respectively.

Table 4
Forecasting results of household 2 load profile, winter, working day

Forecast number	Learning and tuning method	Number of learning and tuning iterations	Type of membership functions	RMSE on validation data set	RMSE on evaluation data set
1	PSO	10	Triangular	0.0800	0.0909
2	PSO	15	Triangular	0.0615	0.0864
3	PSO	20	Triangular	0.0608	0.0863
4	PSO	10	Gaussian	0.0830	0.0863
5	PSO	15	Gaussian	0.0635	0.0868
6	PSO	20	Gaussian	0.0599	0.0852
7	GA	10	Triangular	0.0582	0.0882
8	GA	15	Triangular	0.0649	0.0833
9	GA	20	Triangular	0.0769	0.0862
10	GA	10	Gaussian	0.0628	0.0829
11	GA	15	Gaussian	0.0654	0.0858
12	GA	20	Gaussian	0.0604	0.0857

Table 5
Forecasting results of household 2 load profile, winter, Saturday

Forecast number	Learning and tuning method	Number of learning and tuning iterations	Type of membership functions	RMSE on validation data set	RMSE on evaluation data set
1	PSO	10	Triangular	0.0627	0.0986
2	PSO	15	Triangular	0.0622	0.0993
3	PSO	20	Triangular	0.0612	0.1080
4	PSO	10	Gaussian	0.0615	0.1046
5	PSO	15	Gaussian	0.0648	0.0989
6	PSO	20	Gaussian	0.0625	0.1097
7	GA	10	Triangular	0.0572	0.1062
8	GA	15	Triangular	0.0785	0.1102
9	GA	20	Triangular	0.0657	0.1048
10	GA	10	Gaussian	0.0621	0.1057
11	GA	15	Gaussian	0.0562	0.1091
12	GA	20	Gaussian	0.0613	0.1066

4.3 Graphical Results and Performance Measure

Figures 9 and 10 present the actual and the expected outputs of fuzzy inference system, respectively for forecast number 3 in Table 2 and forecast number 10 in Table 4. In addition, the RMSE value is also shown.

The results shown in Figures 9 and 10 relate only to the validation data. The expected output value is marked in orange, while the actual output value is marked in blue.

Figures 9 and 10 show clearly that regardless of the unique shapes the quality of the forecasts is satisfactory.

After the final FIS was obtained, its performance tests were made. The RMSE (8) was chosen as evaluation metric. The advantage of using RMSE is more penalization of greater errors. The load profile of household 1 on a working day in autumn was used as test data. This time series has not been used before in the FIS training and validation processes. Case 5 from Table 2 was selected as the FIS for testing due to its lowest RMSE error values. Figure 11 shows that obtained RMSE value was 0.065037, which was a slightly higher value than for evaluation data set (0.064200). The reason for the difference in RMSE value is that a tested load profile is slightly dissimilar than load profile used for validation.

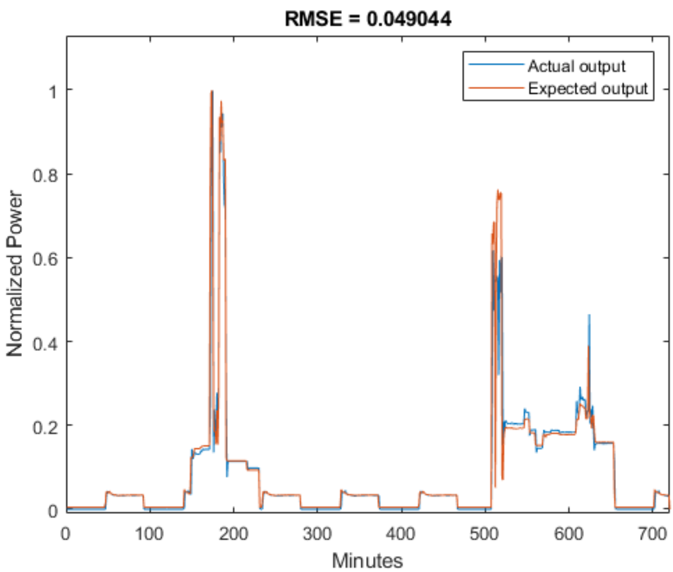

Figure 9

The actual and the expected output of FIS for household 1, working day. Own work

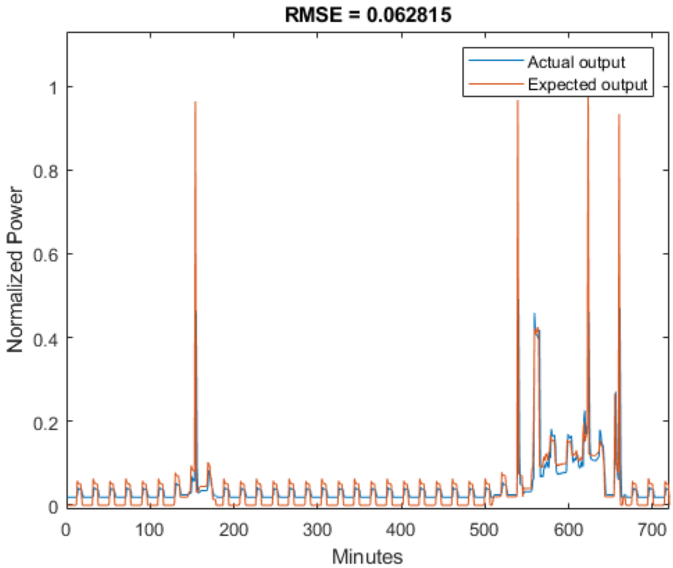

Figure 10
The actual and the expected output of FIS for household 2, working day. Own work

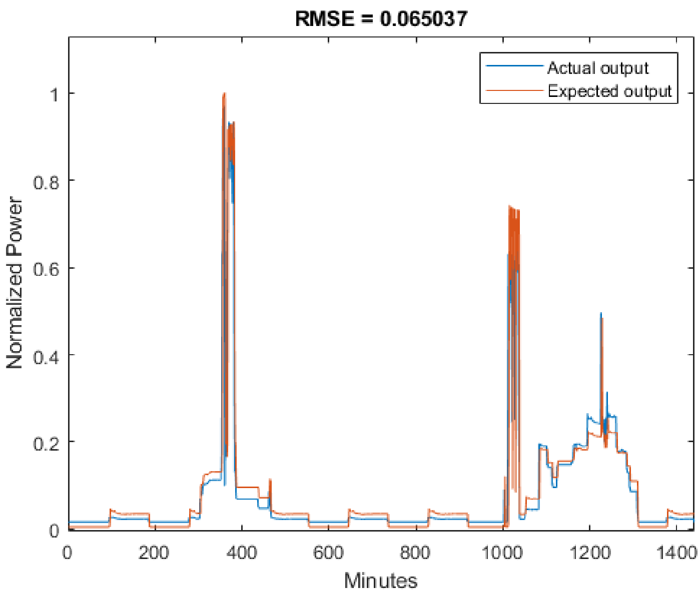

Figure 11
The actual and the expected output of FIS for household 1 – performance measure, autumn working day. Own work

4.3 Discussion

From the data analysis in Tables 2-5, it can be found that for each of the cases, the RMSE values were smaller for the validation data than for the evaluation data. This is a typical feature of forecasting systems. The largest RMSE value was 0.1165 – the forecast number 12 in Table 3. The smallest was 0.0642 – the forecast number 5 in Table 2.

In general, the results of the forecasts for household 2 had higher RMSE values than for household 1, which could have been caused by more sharp shapes in the load profile.

The results of the forecasts 1-3 in Table 2 show that the increase in the number of iterations during learning and tuning does not reduce the RMSE value for the evaluation data. The comparison of the forecasts 1-2 and 4-5 in Table 2 shows that the Gaussian membership functions allow to obtain a slightly lower RMSE value. However, this conclusion does not apply to the corresponding results from Table 4 for household 2, where many sharp shapes in the load profile were less suited for the Gaussian function.

Comparing the results in terms of the learning and tuning method used, it can be concluded that the Particle Swarm Optimization was always better than the Genetic Algorithm. The lower RMSE values obtained by PSO than by GA confirmed this fact. GA is discrete in nature while PSO is continuous. Dense load profiles with an interval of 1 minute can be treated to some extent as continuous signals, which may favor the advantage of PSO over GA in the forecasting process.

The analysis of data in Table 3 and Table 5 shows that the forecasts for non-working day (Saturday) were less accurate than for a working day. Additional temporary shapes in the load profile may be responsible for this fact. The increase in the number of irregular shapes contributes to the deterioration of the forecast quality.

The results of the forecasts for household 2 (Table 4 and Table 5) turns out to be less precise than for household 1 (Table 2 and Table 3). This is mainly due to the fact the load profiles of household 2 have more dense and sharp shapes than in household 1. Gaussian membership function turns out to be better suitable than triangular when forecasting load profiles contain denser shapes (forecasts 1-6 in Table 4).

Conclusions

This paper presented a tuned Type-2 Fuzzy Inference System for residential power consumer load profiles forecasting. The real, dense and non-averaged load profiles were used for testing the proposed approach. The proposed solution showed the efficient performance for a wide number of different FIS cases.

The described FIS has the following advantages: the ease of construction and relatively short calculation times. These features allow for possible fast modifications in order to better match the input data.

The obtained RMSE values can be compared with the results presented in other related papers. For example, in [20] RMSE for T2FIS was 0.2936, while in [7] it was 0.6145. The better predictability of the input signals (compared to the [20]) or higher load profile resolution (one minute in this study, contrary to half an hour in [7]) can be possible cause of better results.

From the obtained results, it is clear that the mentioned solution can be applied to the similar studies. However, it must be highlighted that the quality of forecasts depends on the load profile shapes. Therefore, the parameters of the fuzzy inference system should be selected carefully taking into account the presence and number of irregular shapes in the load profiles.

The presented studies may be developed further in the future by applying cross-validation or evaluating the influence of other type of reduction methods to the forecast quality.

The research of this type may be valuable for the companies selling electricity. Additionally, this research may prove useful for managing the work of microgrids equipped with renewable energy sources and storage devices. The exact knowledge of the residential load profiles in the microgrid helps obtain a more accurate balancing of electricity load.

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