Jerzy MAŁOPOLSKI, Małgorzata TROJANOWSKA, Krzysztof NĘCKA
University of Agriculture in Krakow
Department of Power Engineering and Agricultural Processes Automation
ul. Balicka 116B, 30-149 Kraków, Poland
e-mail: jerzy.malopolski@ur.krakow.pl

FORECASTING OF THE DAILY DEMAND FOR NATURAL GAS IN RURAL HOUSEHOLDS USING THE METHODS OF ARTIFICIAL INTELLIGENCE PART II. FORECASTING USING FUZZY LOGIC

Summary

In this paper, two fuzzy Takagi-Sugeno models were built to describe daily gas consumption of rural households using the Gaussian and trapezoidal membership function. It was found that the predictive values of both models are similar and satisfactory (MAPE 5.3-5.5%) and slightly better than in the case of the model of neural network when the BFGS algorithm was used for training, as shown in the first section of the study.
***Keywords**: natural gas, short-term forecasts, fuzzy logic*

PROGNOZOWANIE DOBOWEGO ZAPOTRZEBOWANIA NA GAZ ZIEMNY WIEJSKICH GOSPODARSTW DOMOWYCH PRZY WYKORZYSTANIU METOD SZTUCZNEJ INTELIGENCJI CZĘŚĆ II. PROGNOZOWANIE PRZY WYKORZYSTANIU LOGIKI ROZMYTEJ

Streszczenie

W pracy przedstawiono zbudowane dwa rozmyte modele typu Takagi-Sugeno opisujące dobowe zużycie gazu przez wiejskie gospodarstwa domowe, wykorzystując gaussowską i trapezoidalną funkcję przynależności. Stwierdzono, że wartość predykcyjna obydwu modeli jest podobna oraz zadowalająca (MAPE rzędu 5,3-5,5%) i nieznacznie lepsza od modelu neuronowego, gdy do uczenia sieci zastosowano algorytm BFGS, a który przedstawiono w części I opracowania.
***Słowa kluczowe**: gaz ziemny, prognozy krótkookresowe, logika rozmyta, modele Takagi-Sugeno*

1. Introduction

Methods of artificial intelligence, in addition to artificial neural networks, include fuzzy logic. In contrast to the artificial neural networks, fuzzy logic has not been used so far in our country to predict demands for natural gas, although it is a convenient mathematical tool which allows to describe the uncertainty and inaccuracy of input data that are always associated with the process of forecasting. Some individual attempts to use fuzzy inference can be found in foreign literature on artificial neural networks [1, 2, 8].

Among the common fuzzy models, inference Takagi-Sugeno models are best suited to forecasting [9], as they best reflect the variation of the studied processes. Their advantage is to provide overt objective knowledge about the system under study. In particular, they are often used in the case of discrete empirical data.

2. Aim and scope of the paper

The aim of the study was the use of the theory of fuzzy sets to predict natural gas demands and, in particular, to develop Takagi-Sugeno models describing the daily gas consumption of rural households and to analyze their usefulness for short-term predicting.

The scope of the paper also includes comparing the quality of predictions built, as based on fuzzy models, and the neural models presented in the first section of this paper [5].

3. Material and methods

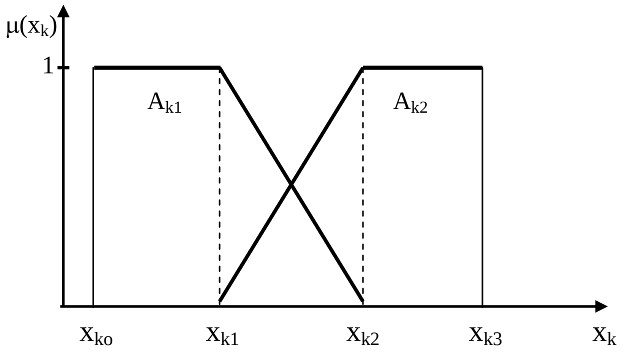
Fuzzy models of daily demands for natural gas are built with the same measurements as the neural models discussed in the first section of this paper [5]. Fuzzy models also adopt the same and input variables and the output variable and the training and test sets as the neural models.
In the process of creating the Takagi-Sugeno model, as at designating any fuzzy model, fuzzification, inference and defuzzification are distinguished.

Fuzzification is the calculation of the degree of fuzzy model input membership to each set. The study used two ways to determine the membership function of these sets. The first one determined fuzzy sets A_i ($i = 1, .., m$) of symmetrical Gaussian membership functions in the three-dimensional universe of discourse of the Takagi-Sugeno model input (TSg) to obtain a model with one fuzzy input and one fuzzy output (the so-called SISO system). The standard deviation of the membership functions of the A_i set was the third of the c_i distance of the center of this function from the center of the nearest neighbour [7].

A Takagi-Sugeno model of trapezoidal membership functions (TSt) was also analyzed in the universe of discourse of the output variables of the models with three fuzzy inputs and one fuzzy output (the so-called MISO system). In these models, three-dimensional universes of discourse of the input variables were divided into two or three fuzzy subsets A_{ki} with trapezoidal membership functions meeting the condition of unit division. Figure 1 shows the breakdown for two fuzzy subsets.
Inference or fuzzy inference is to calculate the value of the output variable based on fuzzy input variables by a set of fuzzy rules. The Takagi-Sugeno models presented in the paper have the following rule bases:
a) TSg model
R1: IF (x_1 near c_{11}) AND ... AND (x_r near c_{1r}) THEN

$(y = a_{10} + a_{11}x_1 + ... + a_{1r}x_r)$, (1)
Rm: IF (x_1 near c_{m1}) AND ... AND (x_r near c_{mr}) THEN ($y = a_{m0} + a_{m1}x_1 + ... + a_{mr}x_r$),
where:
$x_1, ..., x_r$ – input data,
y – output data,
$c_{i1}, ..., c_{ir}$ – the coordinates of the center of the set A_i,
a_{ik} – the coefficients of the linear function,
i = 1, …, m; k = 1, …, r; r = 3.

b) TSt model
R1: IF ($x_1 = A_{11}$) AND ... AND ($x_r = A_{r1}$) THEN ($y = a_{10} + a_{11}x_1 + ... + a_{1r}x_r$), (2)
Rm: IF ($x_1 = A_{1m}$) AND ... AND ($x_r = A_{rm}$) THEN ($y = a_{m0} + a_{m1}x_1 + ... + a_{mr}x_r$),
where:
A_{ki} – reference fuzzy sets in the universes of discourse, $X_1, ..., X_r$,
a_{ik} – the coefficients of the linear function, as in formula 1,
i = 1, …, m ; k = 1, ..., r ; r =3.



Source: Own work / Źródło: opracowanie własne

Fig. 1. Distribution of the universe of discourse X_k into two fuzzy subsets
Rys. 1. Podział przestrzeni rozważań X_k na dwa podzbiory rozmyte

In the Takagi-Sugeno models, the system output y (defuzzification) is calculated as the weighted average value of the function $f_1(x), ..., f_m(x)$, where the weights are the degrees of conclusion activation of the rules R1, ..., Rm (weights are formed of degrees of activation conclusion).

Model parameters were determined using the conjugate gradient method [3, 6], minimizing the sum of squared errors on training sets. When selecting the optimal model, the algorithm for determining the structure of the models presented in the work by Małopolski and Trojanowska [4] was used. This procedure has been developed basing on the constructive principle [7].

The prognostic value of the constructed models was evaluated on the basis of the *APE* and *MAPE* error values [5].

4. Results

Models describing the functional relationship $x_t = f(x_{t-1}, T_{t-1}, d_t)$ were built, where x_t was gas consumption on the t-th day, T_t was the average temperature on the t-th day, and d_t was the day of the week. Using the algorithm for determining the structure of models, the Takagi-Sugeno model with Gaussian membership functions in the universes of discourse of the input variable with six rules was obtained and the Takagi-Sugeno model with trapezoidal membership functions in the universes of discourse X_1, X_2, X_3 of output variables with eight rules. Results of the calculations of the models' parameters are summarized in Tables 1 and 2.

Basing on the developed models, expired forecasts were determined for daily demands for natural gas, to be compared with the values of the actual consumption. Calculations were made separately for the training and test set, thus evaluating the acceptability and accuracy of the predictions (Tab. 3).

The results obtained allow to consider the predictions as satisfactory [10].

Table 1. Results of TSg model estimation of daily gas consumption
Tab. 1. Wyniki estymacji modelu TSg dobowego zużycia gazu

c_{11}	c_{12}	c_{13}	c_{21}	c_{22}	c_{23}	c_{31}	c_{32}	c_{33}
696.2	–1.3	3.0	683.5	–9.3	4.0	374.5	5.3	5.7
c_{41}	c_{42}	c_{43}	c_{51}	c_{52}	c_{53}	c_{61}	c_{62}	c_{63}
382.3	11.2	7.0	250.2	20.1	1.5	264.9	20.4	2.5

a_{10}	a_{11}	a_{12}	a_{13}	a_{20}	a_{21}	a_{22}	a_{23}	a_{30}	a_{31}	a_{32}	a_{33}
187.6	0.7	6.6	–4.2	575.4	0.2	–19.1	–15.5	63.2	0.8	–4.0	10.7
a_{40}	a_{41}	a_{42}	A_{43}	a_{50}	a_{51}	a_{52}	a_{53}	a_{60}	a_{61}	a_{62}	a_{63}
383.3	0.7	–2.3	43.3	27.5	0.9	–1.5	11.6	55.4	0.8	2.3	7.6

Source: Own work / Źródło: opracowanie własne

Tabela 2. Results of TSt model estimation of daily gas consumption
Tab. 2. Wyniki estymacji modelu TSt dobowego zużycia gazu

x_{10}	x_{11}	x_{12}	x_{13}	x_{20}	x_{21}	x_{22}	x_{23}	x_{30}	x_{31}	x_{32}	x_{33}
163.3	473.4	818.4	1070.0	–19.8	–4.4	14.1	24.8	1.0	6.0	6.5	7.0

a_{10}	a_{11}	a_{12}	a_{13}	a_{20}	a_{21}	a_{22}	a_{23}
224.6	0.7	– 6.5	– 0.1	6.5	0.6	9.1	32.0
a_{30}	a_{31}	a_{32}	a_{33}	a_{40}	a_{41}	a_{42}	a_{43}
15.5	0.9	– 0.1	2.4	23.2	0.6	– 1.5	8.7
a_{50}	a_{51}	a_{52}	a_{53}	a_{60}	a_{61}	a_{62}	a_{63}
368.0	0.4	– 12.1	7.3	10.4	0.7	– 8.9	14.9
a_{70}	a_{71}	a_{72}	a_{73}	a_{80}	a_{81}	a_{82}	a_{63}
246.0	0.6	26.9	– 29.8	63.2	0.9	– 48.8	173.5

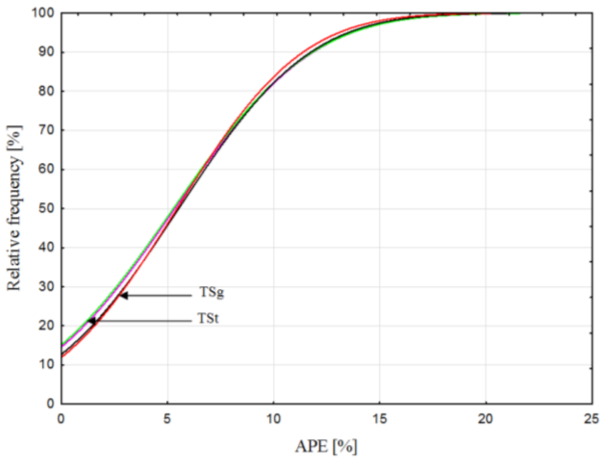
Source: Own work / Źródło: opracowanie własne

For a more complete verification of the quality of predictions, error distributions of daily gas consumption predictions were also analyzed. Error distributions of the predictions are shown in Figure 2. As is apparent from the figure, more than 80% of the predictions have errors below 10% and the errors below 5% characterize nearly half of the predictions.

Table 3. Assessment of the acceptability and accuracy of predictions
Tab. 3. Ocena dopuszczalności i trafności prognoz

Predictive model	*MAPE* [%]	
	training set	test set
TSg	5.35	5.53
TSt	5.27	5.45

Source: Own work / Źródło: opracowanie własne



Source: Own work / Źródło: opracowanie własne

Fig. 2. Empirical distribution prediction errors, as determined basing on the Takagi-Sugeno models using the Gaussian and trapezoidal membership functions
Rys. 2. Dystrybuanty empiryczne błędów prognoz wyznaczonych w oparciu o modele Takagi-Sugeno wykorzystujące gaussowską i trapezoidalną funkcję przynależności

5. Conclusions

In this paper, two Takagi-Sugeno models were built for daily demands for natural gas in rural households, using the Gaussian and trapezoidal membership functions. There was no significant difference in the usefulness of these models for predictive purposes. MAPE prediction errors were at the level of 5.3-5.5% and they were close to the prediction error values set out in the first section of the paper [5] with the best neural model, when the BFGS algorithm was applied to network training.

Further research of the authors will focus on verifying whether the use of a different optimization method improves the quality of fuzzy models, as was the case with artificial neural networks.

6. References

[1] Azadeh A., Asadzadeh S.M., Ghanbari A.: An adaptive network-based fuzzy inference system for short-term natural gas demand estimation: Uncertain and complex environments. Energy Policy, 2010, 38, 1529-1536.

[2] Behrouznia A., Saberi M., Azadeh A., Asadzadeh S.M., Pazhoheshfar P.: An adaptive network based fuzzy inference system-fuzzy data envelopment analysis for gas consumption forecasting and analysis: the case of South America. In: International conference on intelligent and advanced systems. ICIAS 2010, Article number 5716160. et al.

[3] Findeisen W., Szymanowski J., Wierzbicki A.: Teoria i metody obliczeniowe optymalizacji. Warszawa: WNT, 1977.

[4] Małopolski J., Trojanowska M.: Modele rozmyte zapotrzebowania na moc dla potrzeb krótkoterminowego prognozowania zużycia energii elektrycznej na wsi. Część I. Algorytmy wyznaczania modeli rozmytych. Inżynieria Rolnicza, 2009, 5 (114), 177-183.

[5] Nęcka K., Trojanowska M. Małopolski J.: Forecasting the daily demand for natural gas in rural households using the methods of artificial intelligence. Part I. Forecasting using artificial neural networks. Journal of Research and Applications in Agricultural Engineering, 2015, 2.

[6] Osowski S.: Sieci neuronowe w ujęciu algorytmicznym. Warszawa: WNT, 1996.

[7] Piegat A.: Modelowanie i sterowanie rozmyte. Warszawa: AOW EXIT, 1999.

[8] Soldo B.: Forecasting natural gas consumption. Applied Energy, 2012, 92, 26-37.

[9] Takagi T. Sugeno M.: Fuzzy identification of systems and its applications to modelling and control. IEEE Transactions on Systems, Man, and Cybernetics, 1985, 15(1), 116-132.

[10] Zeliaś A., Pawełek B., Wanat S.: Prognozowanie ekonomiczne. Warszawa: PWN, 2004.