THE SHORT-TERM FUZZY LOAD PREDICTION MODEL

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ABSTRACT

This article describes the influence of the kind of membership function on the accuracy of fuzzy logic forecasting model in the local power system. Fuzzy logic approach overcomes some problems related to practical implementations of traditional modelling and forecasting methods. This qualitative method of load forecasting can incorporate imprecise and ambiguous information in reasoning. The combination of fuzzy logic and other deterministic or stochastic methods which has recently emerged as a highly promising approach for electric load forecasting is also discussed. This paper describes the prediction algorithms and methods employed and points out the benefits gained by the use of the method.

Keywords: *short term load forecasting, electric power engineering, similarity-based methods, fuzzy logic.*

1. INTRODUCTION

Recently, either in Poland [1, 5-8] or in other countries [2-4] a trend can be observed towards applying alternative methods of mathematical modelling, including artificial intelligence tools (SSN, GA, FL, FS and all sorts of their hybrids). One of the reasons of such a rapid development of the above mentioned techniques is their effectiveness by far exceeding that of the so-called classical models.

Conventional mathematical procedures require giving non-ambiguous input information, what severely limits the predictive power of forecasts, projects, models, etc. In response to the needs of science and technology, professor L.A. Zadeh developed the foundations of fuzzy sets theory in 1965 (in an article titled 'Fuzzy Sets' he introduced the idea and first theoretical concepts). It gave rise to a new branch of mathematics dealing with the processing of imprecise information. Even though the expansion of this theory was initially hampered due to the dramatically increasing interest in digital technology based on binary logic, the last decade of the 20th century witnessed a dynamic development of research on methods of fuzzy modelling to be applied in controlling, optimization, decision-making, diagnosing and monitoring, pattern recognition and many others. During this time a number of publications appeared, where fuzzy logic was used for planning as well as for development [4].

2. FUZZY PREDICTION MODEL

The main advantage of fuzzy models in comparison to conventional mathematical models is that the former can be developed on the basis of much less complete information on the system. The information can be fuzzy and imprecise, such as typically encountered in local power systems. A number of factors contributing to this situation are discussed in [1], including difficulties related to the transformation of power management, new companies operating in the energy market, fluctuations in the prices of electrical energy after the state regulation of prices gave way to market mechanisms, crises etc. The authors of the above mentioned publications also suggest innovative methods of prognosing.

The present paper offers an implementation of one of the most popular fuzzy models – the Mamdani model. The model aims at mapping the input vector X to the output Y so that the mapping is as close as possible with respect to the mean absolute error to the mapping X→Y realized by the system. This method of predicting is based on the classical fuzzy model with two inputs and one output presented in Fig. 1.

Two sharp values x_1, x_2 are given as input to the fuzzy model and modified by the subsequent modules of the model so that the sought response of the model to the prescribed values is obtained at the output.

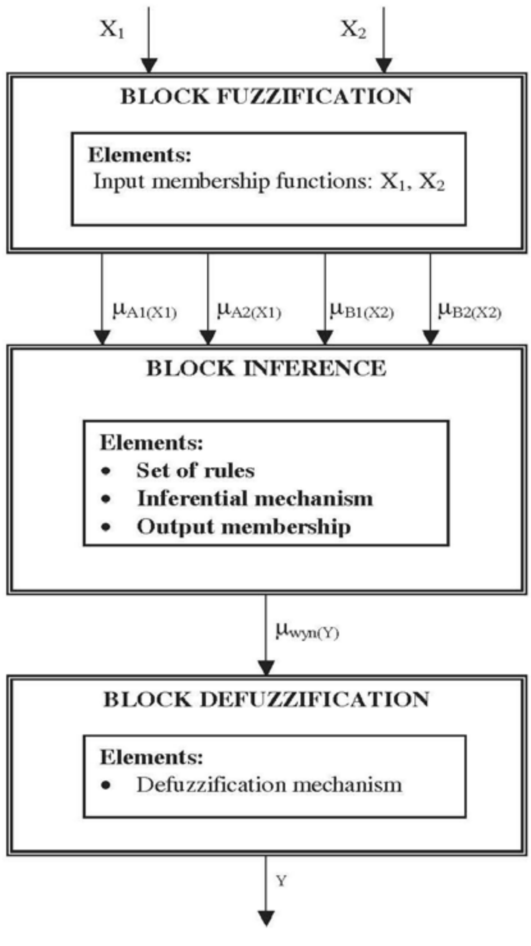

Fig. 1 Block diagram of the classical fuzzy model of the 2 input/1output system.

2.1. Fuzzification

In this module the following operations are carried out: fuzzifying the real values input to the model and calculating the membership degrees of inputs to fuzzy sets A_i and B_j. To enable these operations, the membership functions $\mu_{Ai}(x_1)$, $\mu_{Bj}(x_2)$ in the fuzzy sets of the particular inputs have to be precisely defined for the module "Fuzzification".

The data used in the experiments was the 24-hour load in the day-by-day routine of a selected distribution company in 2000 and 2001. The loads examined were decomposed to isolate for forecasting only one weekday, specifically Wendesday, from the summer months. The real input value x_1 in the model was the hour load of the local system in the h-th hour of the day for the t-2 week, and the real input value x_2 was the hour load of the same hour for the t-1 week.

The problem to be examined was whether the type of membership function influences the prediction model described above. From among a number of membership functions applied in fuzzy models [5, 8] two were chosen: segmentally linear functions summing up to 1, and the Gauss symmetrical function.

The choice was motivated by the need to transmit true information included in the assumptions and conclusions of the rules of the Mamdani model based on these membership functions. It is not always the case that the prediction model with the smallest error of discrepancy between the model and the reality is the optimum model for forecasting.

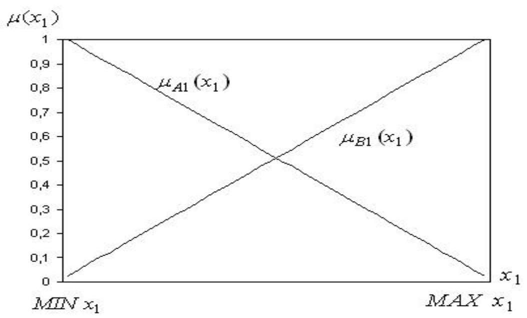

Fig. 2 Segmentally linear membership functions of input to the fuzzy set A_i.

Linear membership functions can be obtained by bilateral bounding of the variation interval of the variables x_1 and x_2. In the experiment conducted both the variables represented the hourly load of the local power system in a given time interval. Therefore for a selected calibration period of the model, a uniform amplitude of variable fluctuations can be established between the minimal and maximal values in the interval $Amp = Max\ x - Min\ x$. The membership degrees are to be obtained from

$$\mu_{A1}(x_i) = \frac{Amp - |x_i - Min\ x|}{Amp},\ dla\ i = 1,2.$$
$$\mu_{B1}(x_i) = \frac{Amp - |x_i - Max\ x|}{Amp},\ dla\ i = 1,2. \quad (1)$$

Where:

Amp - the amplitude of the variable fluctuations x_1 and x_2,

x_i – the sharp values inputs to the fuzzy system.

Fig. 3. presents the course of the Gauss symmetrical functions which provided the basis for establishing functions of set membership from Eqn. (1).

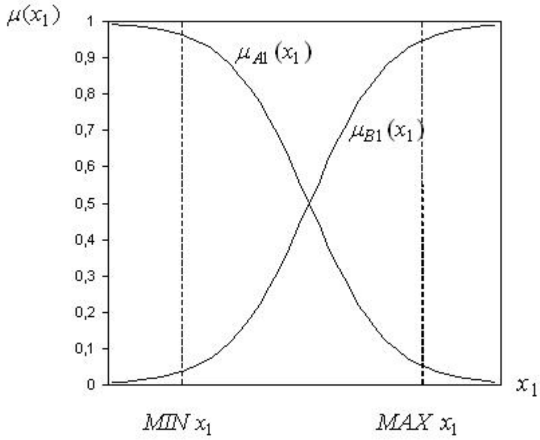

Fig. 3 The Gauss membership functions of inputs to the fuzzy set A_i.

The Gauss membership functions were obtained from

$$\mu_{A1}(x_i) = e^{-\left(\frac{x_i - Min\ x}{Amp}\right)^2},\ dla\ i = 1,2.$$
$$\mu_{B1}(x_i) = e^{-\left(\frac{x_i - Max\ x}{Amp}\right)^2},\ dla\ i = 1,2. \quad (2)$$

Where

A_{mp} is the width of the Gauss function.

2.2. Inference

In this module the resultant membership output function $\mu_{wyn}(y)$ is calculated on the basis of the input membership degrees $\mu_{Ai}(x_1)$, $\mu_{Bj}(x_2)$ in the fuzzy sets of the respective inputs. The function, which often takes a complex form, has to be calculated on the basis of strictly determined elements. The first of the considered elements in the set of rules, containing logical rules determining the cause-effect relations existing between the fuzzy input and output sets in the system.

The set of rules can be described in the following way, using the expressions 'small', 'increases', decreases', and 'large':

$$R1:\ If\ (x_1 = A_1)\ I\ (x_2 = B_1)\ then\ (y = \text{"small"})$$
$$R2:\ If\ (x_1 = A_1)\ I\ (x_2 = B_2)\ then\ (y = \text{"increases"})$$
$$R3:\ If\ (x_1 = A_2)\ I\ (x_2 = B_1)\ then\ (y = \text{"decreases"}) \quad (3)$$
$$R4:\ If\ (x_1 = A_2)\ I\ (x_2 = B_2)\ then\ (y = \text{"large"})$$

Applying the above mentioned expressions-labels in the model is hardly possible for a large number of fuzzy sets (for each hour of day and night, ten weeks). Thus, in accordance with the suggestions offered in [5] the actually applied are fuzzy numbers in the form 'approximately $= C_i$', where C_i is a given fuzzy number representing the expression 'small$= C_1$', 'increases$= C_2$', decreases$= C_3$', 'large$= C_4$', defined individually for each fuzzy set.

$$\begin{aligned} &R1: \ If \ (x_1 = A_1) \ I \ (x_2 = B_1) \ then \ (y = C_1) \\ &R2: \ If \ (x_1 = A_1) \ I \ (x_2 = B_2) \ then \ (y = C_2) \\ &R3: \ If \ (x_1 = A_2) \ I \ (x_2 = B_1) \ then \ (y = C_3) \\ &R4: \ If \ (x_1 = A_2) \ I \ (x_2 = B_2) \ then \ (y = C_4) \end{aligned} \qquad (4)$$

The resultant membership function $\mu_{wyn}(y)$ in the inference module is realized by the inferential mechanism. As the first step, the degrees are calculated to which the assumptions of particular rules are fulfilled, next, the degree to which the conclusions of particular rules are activated. As the last stage, the resultant form of the membership function is calculated on the basis of the degree of rule activation.

The membership function can be obtained by means of a number of operators of fuzzy implication. One of the most frequently used operators is the Mamdani operator MIN. Its basic rule is that the truth of the conclusion cannot be greater than the degree of fulfilling an assumption. This operator, however, has some disadvantages, which tend to reduce the range of its applications. According to [6] (on the basis of a survey conducted at the conference 'Fuzzy Control' in Witten, Germany in 1995) most specialists working in the field prefer the operator PROD, having the form of a logical product, to the operator MIN.

For the reason stated above the logical product operator PROD was chosen for the experiment. It is defined as

$$\mu_{A\cap B}(y) = \mu_{wyn}(y) = \mu_A(x)\cdot\mu_B(x), \forall x \in X \qquad (5)$$

2.3. Defuzzification

On the basis of the resultant membership function $\mu_{wyn}(y)$ a sharp output value is determined from the sharp input values x_1 and x_2. From among a number of existing defuzzification methods the height method was selected. Its idea is presented in Fig. 4.

In this method each fuzzy set of the model output is replaced by a singleton μ_C placed within the modal value of this set. The result of defuzzification, depending on the number of rules, is obtained from

$$y = \frac{\sum_{j=1}^{m} y_j \mu_{C,j}}{\sum_{j=1}^{m} \mu_{C,j}} \qquad (6)$$

where – m is the number of rules.

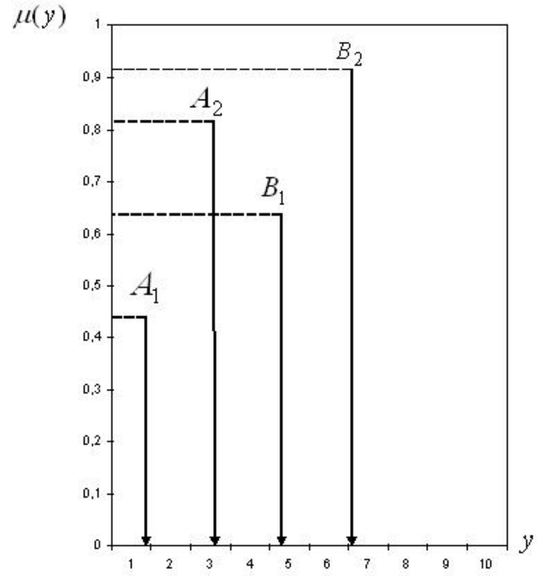

Fig. 4. Defuzzification by means of the height method.

3. THE VERIFICATION OF THE MODEL

The model was verified for a selected local power system. The data, initially comprising the 24h loads of the system in 2000 and in 2001, was subsequently decomposed so that working Wednesdays from the summer months (June, July, and August) were selected for further testing. The fuzzy prediction model was calibrated for the data of the year 2000 by modifying the rules for each hour of the 24h cycle so that the average error between the output value and a real value was minimized.

Then, input values from the year 2001, as described by Eqn.1, are introduced to the calibrated model to obtain the response of the model at the output, corresponding to the sought forecast value. The forecasts were made in one-week advance period.

As mentioned, two kinds of activation functions were employed in the tests. Subsequently, the influence of the kind of function chosen on the accuracy of prediction was analysed.

Additionally, a model of multiple regressions in the form

$$y_t = \alpha_0 + \alpha_1 P_{h,t-1} + \alpha_2 P_{h,t-2} + \xi_t \qquad (7)$$

where:

- t – is the index of the week number (t=1..9),
- h – is the index of hour number in the 24 hours cycle (h=1..24),
- $\alpha_0, \alpha_1, \alpha_2$ - are parameters obtained with the least square method,
- ξ - is a coefficient representing random factor, was develop for comparison of the obtained results.

The model was verified for the same variables and for the same time period.

Table 1 The accuracy of calibrating the fuzzy prediction models for 2000.

Membership function	Accuracy of calibration
Linear	2,54%
Gauss	2,28%

The results of error analysis for the 24h forecasts prepared in one-week advance for the selected power system are presented in tab.2.

Table 2 Error analysis for an empirically verified forecast in the selected power system in 2001.

		Membership function		Regression
		Linear	Gauss	
N		216	216	216
MPE	[%]	0,694	3,792	-5,383
MAPE	[%]	3,553	4,372	6,181
RMSPE	[%]	4,921	5,472	7,843
SDPE	[%]	4,882	3,951	5,713
Min APE	[%]	0,022	0,056	0,004
Max APE	[%]	16,023	18,162	24,961

The symbols used in tab.2. represent:

N - The number of times a forecast was verified,
PE - Percentage Error,
APE - Absolute Percentage Error,
MPE - Mean Percentage Error,
MAPE - Mean Absolute Percentage Error,
RMSPE - Rot Mean Square of Percentage Error,
SDPE - Standard Deviation of Percentage Error.

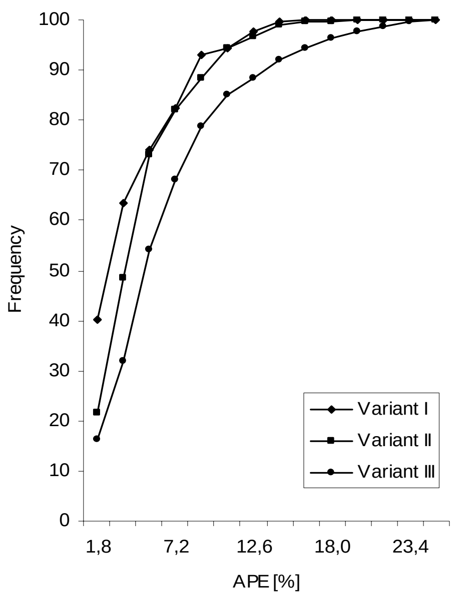

Fig. 5 Distribution function of error occurrence.

4. CONCLUSION

The results obtained by the empirical verification of forecasts with the data measured demonstrate beyond any doubt that using the segmentally linear membership functions yields more accurate results than the Gauss membership function: MAPE=3,55% versus MAPE=4,37%, respectively. It confirms the validity of the claim presented in [8], that the membership functions applied in the fuzzy model should have a finite carrier and 'truth-telling' rules. The Gauss functions do not satisfy this condition.

As far as the accuracy of forecasting is concerned, the prediction model constructed on the basis of fuzzy logic meets accuracy requirements similar to those of forecasting models based on classical prediction methods as well as of models applying unconventional techniques.

It appears possible to further improve the forecasting accuracy of the model by including, as input variables, metrological factors and other quantities determining the load of local power systems.

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BIOGRAPHY

Tomasz Popławski was born on 7.03.1965. In 1991 he graduated (MSc.) with distinction at the Institute of Power Engineering of the Faculty of Electrical Engineering at Technical University in Czestochowa. He defended his PhD. in the field of methods of analysis and forecast of power engineering in 2000; his thesis title was " Structural forecasting of loads in power systems ". Since 2006 he is working in the Institute of Power Engineering. He is a chief in the ZIMEiGE team. His scientific research is focusing on the forecast and analyse methods use to the power systems. In addition, he also investigates AI technics using it to forecast.