Libor ŽÁK*David VALIŠ**

# FUZZY INFERENCE SYSTEM AND PREDICTION

**Keywords:** fuzzy sets, fuzzy logic, fuzzy inference system, prediction implementation, employees

## ABSTRACT

This paper describes the implementation of fuzzy set theory and Fuzzy Inference System (FIS) for prediction of electric load. The proposed technique utilizes fuzzy rules to incorporate historical weather and load data. The use of fuzzy logic effectively handles the load variations due to special events. The fuzzy logic has been extensively tested on actual data obtained from the Czech Electric Power Company (ČEZ) for 24-hour ahead prediction. Test results indicate that the fuzzy rule base can produce results better in accuracy than artificial neural networks (ANNs) method.

## 1. INTRODUCTION

Short-term load forecasting (STLF) of power demand plays a very important role in the economic and secure operation of power systems [1]. Improvement in accuracy of load forecasts results in substantial savings in operating cost and also increase the reliability of power supply. In order to predict the future load accurately, numerous forecasting techniques have been used during the past 40 years.

Fuzzy logic model has been selected as an alternative method for the load forecasting problem in this paper. It is a suitable technique in case when the historical data are not real numbers, but linguistic values [4]. This paper presents the results of a preliminary investigation of the feasibility of use of a fuzzy logic model for short-term load forecasting. In this research, historical load and weather data are converted into fuzzy

* University of Technology in Brno Mathematical Institute Technická 2, 616 69, Brno Czech Republic zak.l@fme.vutbr.cz

** University of Defence in Brno Department of Combat and Special Vehicles Kounicova 65, 662 10, Brno, Czech Republic david.valis@unob.cz

set theory to produce fuzzy forecasts and defuzzification is performed to generate a point estimate for system load.

## 2. FUZZY INFERENCE SYSTEM

Fuzzy set is one, which has vague boundaries. Fuzzy sets can successfully represent a human's ambiguous estimations. They are represented by a membership function, which takes values between 0.0 and 1.0. Fuzzy reasoning uses this membership function to describe the human's reasoning process successfully.

### 2.1. DESCRIPTION OF FUZZY INFERENCE SYSTEM

**Fuzzy set** A is defined in terms $(U, \mu_A)$, where $U$ is relevant universal set and $\mu_A U \rightarrow < 0, 1 >$ is a membership function, which assigns each elements from $U$ to fuzzy set $A$. The membership of the element $x \in U$ of a fuzzy set $A$ is indicated $\mu_A(x)$. We call $F(U)$ the set of all fuzzy set. Then „classical" set $A$ is fuzzy set where: $\mu_A : U \rightarrow \{0, 1\}$. Thus $x \in A \Leftrightarrow \mu_A(x) = 0$ and $x \notin A \Leftrightarrow \mu_A(x) = 1$ . Let $U_i, i = 1, 2, ..., n$, be universals. Then fuzzy relation $R$ on $U = U_1 \times U_2 \times ... \times U_n$ is a fuzzy set R on universal U.

**Fuzzy Inference System**: One of the possible applications is a **fuzzy inference system** (FIS) (fuzzy regulator). There are a few types of regulators. We use the regulator of type $P : u = R(e)$ for our purposes, where the action values depend only on a regulation deviation:

Input variables: $E_i = (E_i, T(E_i), E_i, G, M), i = 1, ..., n$.

Output variables: $U = (U, T(U), U, G, M)$.

We consider the fuzzy regulator as the statement of the type: $\Re = \Re_1$ else $\Re_2$ else ,..., else $\Re_p$, where $\Re_k$ is in the form: $\Re_k = if e_1$is $X_{E_1,k}$ and $e_2$is $X_{E_2,k}$ and ... and $e_n$ is then $u$ is $Y_{U,k}$, where $e_1 \in E_1, ..., e_n \in E_n, u \in U$, $X_{E_i,k} \in T(E_i)$, $Y_{U,K} \in T(U)$ for $\forall i = 1, ..., n$, for $\forall k = 1, ..., p$.

We mark meaning of the mathematical statement $\Re$ by $M(\Re) = R$. $M(\Re)$ and the fuzzy relation on $E_1 \times E_2 \times ... \times E_n \times U$ is defined by $R = M(\Re) = \bigcup_{k=1}^{p} M(\Re_k)$, where else it is considered as an union and $M(\Re_k)$ is defined in the form: $M(\Re_k) = A_{E_1,k} \times A_{E_2,k} \times ... \times A_{E_n,k} \times A_{U,k}$. This is the fuzzy relation on $E_1 \times E_2 \times ... \times E_n \times U$, where $A_{E_i,k} = M(X_{E_i,k})$ is the fuzzy set on universal $E_i$ for $\forall i = 1, \ldots, n$ and $A_{U,k} = M(Y_{U,k})$ is the fuzzy set on universal $U$ for $\forall k = 1, \ldots, p$.

Let $a_{E_i}$ $i = 1, \ldots, n$ be a regulation deviance. Let $a_{E_i}$ be any fuzzy set on $E_i$.

Then the dimension of action values $a_U$ is defined by term $a_U = (a_{E_1} \times a_{E_2} \times ... \times a_{E_n})^\circ R$. This is a composition of fuzzy relation $(a_{E_1} \times$

$a_{E_2} \times ... \times a_{E_n}$) on universal $E_1 \times E_2 \times ... \times E_n$ and relation $R$ defined on the universal $E_1 \times ... \times E_n \times U$. The result of this composition is the fuzzy set on the universal $U$.

We do not require the output of fuzzy regulator to be a set in many cases, but we require the concrete value $z_0 \in Z$, e.i. we want to make a defuzzification. The centroid method is the most frequently used method of defuzzification. The FIS defined in such a way is called Mamdami.

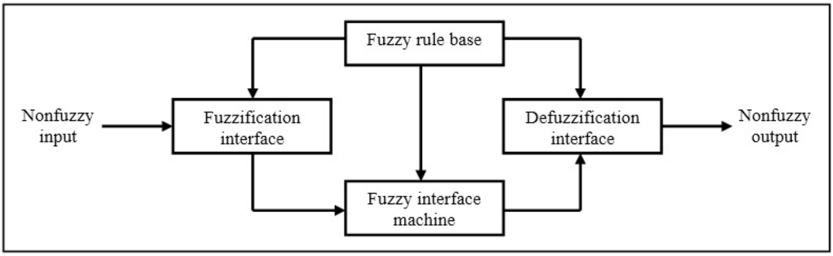


**Fig.** 1. Block diagram of a fuzzy inference system

## 2.2. DESCRIPTION FIS FOR PREDICTION OF LOAD

The four principal components of a fuzzy system is shown in Figure 1. The *fuzzification* interface performs a scale mapping that changes the range of values of input variables into corresponding universe of discourse. It also performs fuzzification that converts nonfuzzy (crisp) input data into suitable linguistic values, which may be viewed as labels of fuzzy sets. *Fuzzy rule* base, which consists of a set of linguistic control rules written in the form "If a set of conditions are satisfied, Then a set of consequences are inferred". *Fuzzy inference machine*, which is a decision-making logic that employs rules from the fuzzy rule base to infer fuzzy control actions in response to fuzzified inputs. *Defuzzification* interface performs a scale mapping that converts the range of values of output variables into corresponding universe of discourse. It also performs defuzzification that yields a nonfuzzy (crisp) control action from an inferred fuzzy control action [2]. A commonly used defuzzification rule known as *centroid method* is used here, according to which the defuzzification interface produces a crisp output defined as the center of gravity of the distribution of possible actions. This centroid approach produces a numerical forecast sensitive to all the rules.

Fuzzy logic is a tool for representing imprecise, ambiguous, and vague information. Fuzzy set operations are grounded on a solid theoretical foundation, although they deal with imprecise quantities, they do so in a most precise, and well-defined way. Fuzzy operations that act on the membership functions lead to consistent and logical conclusion [3]. If we use appropriate membership function definitions and rules, we can achieve useful results. One of the most useful properties of the fuzzy set approach is that contradictions in the data need not cause problems. Fuzzy systems are stable, easily tuned and can be conventionally validated. Designing of fuzzy sets is very easy and simple. Abstract reasoning and human-like responses in cases involving uncertainty and contradictory data are the main properties of fuzzy systems [4].

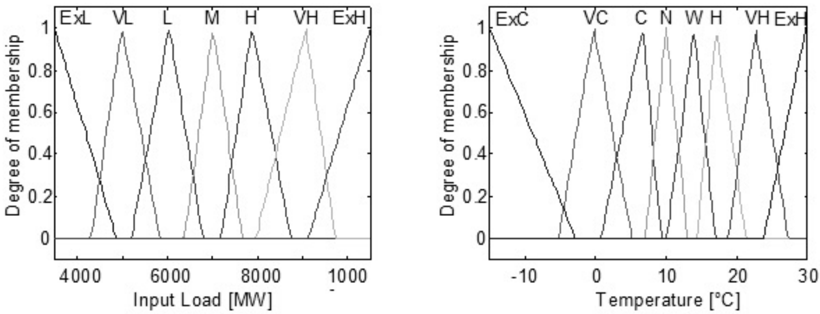


**Fig.** 2. Triangular type membership functions for input load, input temperature

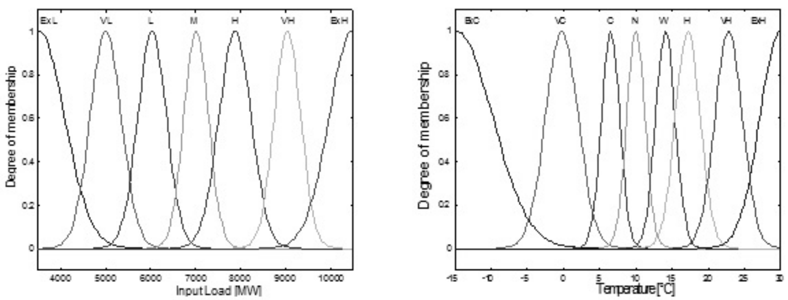


**Fig.** 3. Gaussian curve membership function for input load and input temperature

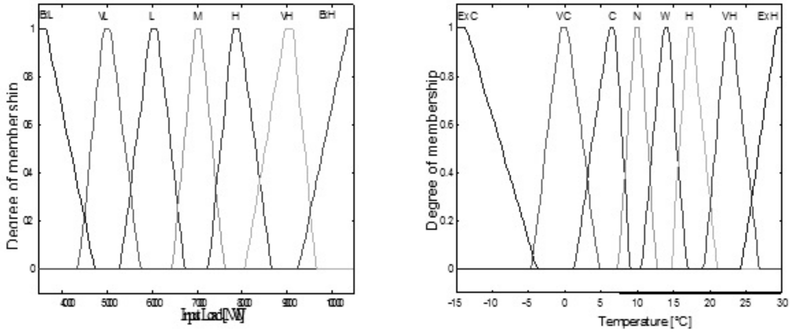


**Fig.** 4. Trapezoidal membership function for input load and input temperature

## 2.3. FUZZY RULES FOR PREDICTION OF LOAD

Heuristic and expert knowledge are often expressed linguistically in the form of If-Then rules. These rules can be extracted from common senses, intuitive knowledge, general principles and laws, and other means that reflect actual situations. For example "If the temperature is extremely cold, Then load demand will be very high" is an example of logic statement. The input temperature is sorted into eight categories and labeled as Extremely Cold (ExC), Very Cold (VC), Cold (C), Normal (N), Warm (W), Hot (H), Very Hot (VH), and Extremely Hot (ExH). The input and output load is sorted into seven categories and labeled as Extremely Low (ExL), Very Low (VL), Low (L), Normal (N), High (H), Very High (VH), and Extremely High (ExH) as shown in Figure 2.

A tentative list of input and output variables using statistical analysis, and engineering judgements was compiled. The input and output variables within the [0, 1] region was normalized. The next step was the selection of the shape of the fuzzy membership for each variable. This is purely arbitrary, but one usually starts with a particular shape of membership function and changes it if the forecasting accuracy is not good. The triangular shaped mappings shown in Figure 2 are very common, however, alternative shapes, such as Gaussian and trapezoidal curve with different amounts of function overlapping, were also used as shown in Figure 3 and 4, respectively.

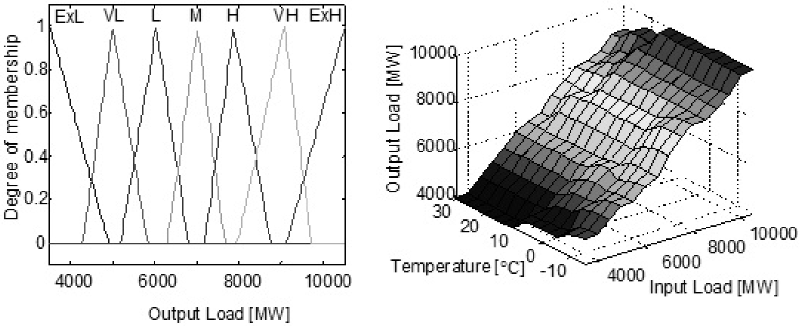


**Fig.** 5. Triangular type membership functions for output load and FIS surface for triangular input.

## 3. TEST RESULTS

Two years of historical load and temperature data were used, one year (1998) for the fuzzy rule base design and the following year (1999) for testing the model performance. The inputs used to forecast hourly load for day $(t)$ are; hourly load of the previous day $(t-1)$ and minimum, maximum and average temperature for the day $(t)$. In case, the accuracy is un-satisfactory, then the number of fuzzy membership functions and/or shape of the fuzzy membership functions can be changed and a new fuzzy rule base is obtained. The iterative process of designing the rule base, choosing a defuzzification algorithm, and testing the system performance may be repeated several times with a different number of fuzzy membership functions and/or different shapes of fuzzy memberships. The fuzzy rule base that provides the minimum error measure for the test set is selected for real-time forecasting.

The quality of prediction of heat consumption has been calculated according to average error $MAPE$. Let $(R_1, R_2, \ldots, R_k)$ be the real values of time series and $(P_1, P_2, \ldots, P_k)$ are the predicted members of time series where $k$ is the number of searched members. Thus

$$MAPE = \frac{1}{k}(\sum_{i=1}^{k}(abs\frac{(P_i - R_i)}{R_i})$$

$$MAP = \max_{i=1,\ldots,k}(abs\frac{(P_i - R_i)}{R_i})$$

**Tab.** 1. MAPE and MAP for working days in 3rd Week of January 1999 using various membership functions

| Days | Membership Functions | | | | | |
|---|---|---|---|---|---|---|
| | Triangular | | Gaussian Curve | | Trapezoidal | |
| | MAPE(%) | MAP(%) | MAPE(%) | MAP(%) | MAPE(%) | MAP(%) |
| Mo. | 2.8 | 6.1 | 2.3 | 8.8 | 2.2 | 4.8 |
| Tu. | 1.3 | 4.7 | 1.1 | 3.9 | 1.4 | 5.4 |
| We. | 0.99 | 2.7 | 1.4 | 4.9 | 1.2 | 3.5 |
| Th. | 0.88 | 2.3 | 1.8 | 4.0 | 1.1 | 2.5 |
| Fr. | 0.89 | 2.4 | 1.6 | 4.3 | 1.2 | 3.2 |

**Tab.** 2. MAPE and MAP for 3rd Weekend in January 1999 using various membership functions

| Days | Membership Functions | | | | | |
|---|---|---|---|---|---|---|
| | Triangular | | Gaussian Curve | | Trapezoidal | |
| | MAPE(%) | MAP(%) | MAPE(%) | MAP(%) | MAPE(%) | MAP(%) |
| Sa. | 3.6 | 8.5 | 5.4 | 7.8 | 6.0 | 8.6 |
| Su. | 3.1 | 7.6 | 4.9 | 8.6 | 6.2 | 9.8 |

Using different membership functions, the mean absolute percentage error ($MAPE$) and maximum absolute percentage error ($MAP$) for working days of the week, weekend and special days are computed as given in Tables 1, 2 and 3, respectively. Similarly, $MAPE$ for each day of the week during $3^{rd}$ week of January 1999 using fuzzy logic and back-propagation neural network is also shown in Figure 6.

**Tab.** 3. MAPE and MAP for special days/holidays during the year 1999 using various membership functions

| Days | Membership Functions | | | | | |
|---|---|---|---|---|---|---|
| | Triangular | | Gaussian Curve | | Trapezoidal | |
| | MAPE(%) | MAP(%) | MAPE(%) | MAP(%) | MAPE(%) | MAP(%) |
| NY[1] | 2.6 | 8.0 | 3.4 | 7.6 | 3.8 | 7.4 |
| E[2] | 3.0 | 7.1 | 3.0 | 8.1 | 2.7 | 6.8 |
| L[3] | 2.6 | 7.8 | 4.0 | 9.2 | 3.3 | 9.2 |
| V[4] | 3.2 | 7.9 | 1.3 | 4.1 | 4.0 | 9.9 |
| Y[5] | 2.0 | 4.1 | 4.8 | 4.4 | 2.2 | 5.6 |
| I[6] | 1.6 | 4.4 | 2.2 | 5.0 | 4.8 | 8.5 |
| S[7] | 2.6 | 5.1 | 1.8 | 6.8 | 2.7 | 5.4 |
| C[8] | 3.1 | 5.6 | 3.6 | 5.1 | 1.7 | 4.4 |
| C1[9] | 3.4 | 8.7 | 4.6 | 8.9 | 4.9 | 7.3 |
| C2[10] | 3.2 | 9.8 | 4.2 | 7.9 | 5.1 | 10.1 |

[1] New year day
[2] Easter
[3] Labor day
[4] Victory day
[5] Yanhose day

To compare the performance of the fuzzy logic model, a back-propagation network (BPN) was also developed. A separate BPN with only one hidden layer and 24 hidden neurons was used for each day using the same inputs and single output as the fuzzy logic model. The training and testing of BPN were performed with the same training and testing data sets as mentioned earlier.

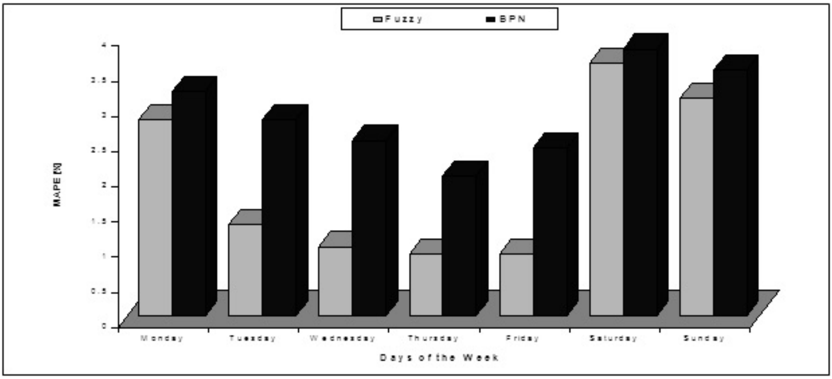


**Fig.** 6. MAPE for each day of the Week during 3rd Week of January 1999 using fuzzy logic and back propagation neural network

## 4. CONCLUSIONS

A forecasting technique based on fuzzy logic approach has been presented in this paper. This approach can be used to forecast loads with better accuracy than ANN technique. The flexibility of the proposed approach, which offers a logical set of rules, readily adaptable and understandable by an operator, may be a very suitable solution to the implementation and usage problem that has consistently limited the adoption of STLF models. This technique is simple to implement on a personal computer and allows for operator intervention. Some inspirational models are in [7-14].

Various membership functions have been discussed, and for the particular application data sets, their effects on model performance have

[6] Independence day
[7] Students' day
[8] Christmas eve
[9] Christmas 1st day
[10] Christmas 2nd day

been demonstrated. The proposed model has been able to generate forecasts with a MAPE frequently below 2.8 % for working days, 3.6 % for weekends and 3.4 % for special days. The simulation results demonstrate the effectiveness of the fuzzy model for 24-hour ahead prediction.

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