A Midterm Energy Forecasting Method Using Fuzzy Logic

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Abstract: - The objective of this paper is to present a new methodology for midterm energy forecasting in the framework of fuzzy logic. This method is based on an already formatted database, which includes values for energy consumption, weather parameters, statistical indices etc. The data is mined from the database in order to be used for the discovery of knowledge through a midterm energy forecasting method, using fuzzy logic. This model can be optimized on the choice of the input data as well as on the number of the triangular membership functions and their base widths. Finally, its results are compared to a non-linear multivariable regression model and to classic regression models for two types of customers, i.e. high voltage industries and residential customers.

Key-Words:- energy midterm forecasting, fuzzy logic, optimization of membership function

1 Introduction

Accurate load forecasting leads to effective scheduling and planning and thus to higher system reliability and lower operational costs. The electricity industry needs forecasts for short term, midterm and long term time horizons.

Many forecasting models and methods have been implemented on load forecasting, with different level of success. In past years electric companies used mostly simple forecasting models like linear regression and simple econometric models of one or two parameters. Nowadays multiple regression models are used for very large systems [1], large metropolitan areas [2] or small areas. Other load forecasting methods take into consideration the use of land as well as their perspective changes [3]. In references [4]-[5] models that forecast the needs of various types of customers are presented. These models are based on the number and use of appliances and they require a large amount of relevant information. Model ARMAX [6] and multiple regression including autocorrelation index and t-test [7] give good results. The study of energy growth for every type of customer separately, is thought to give more accurate results [8]. Recently, application of artificial intelligence techniques has also been carried out [9]. Especially as far as short-term forecasting is concerned, methods based on fuzzy logic have been developed, either directly as in [10] or through the use of the least squares method, or in the form of fuzzy neural networks [11], or even using a hybrid model of neural-fuzzy logic [12]. Even more, models using fuzzy logic based on parameters concerning the use of land in the areas under study have been developed [13].

In this paper a new method for midterm energy forecasting is proposed based on of fuzzy logic. Initially, based on the database developed in [14] the first step of the data mining process (Data knowledge discovery) is carried out. Data finally needed is determined by the proposed method. Optimization of the model is also achieved through the proper formation of the triangular membership functions. The proposed model is implemented for two types of customers, i.e. residential and high voltage industries customers. Results are compared to standard regression methods and to the method presented on [14].

2 Basic Principles of Fuzzy Logic

The mathematical foundation of fuzzy logic is based on the theory of fuzzy sets, which may be considered as a generalization of the classic theory of sets. Fuzziness is a language attribute. Its main origin is the ambiguity that exists in the definition and use of symbols. The switch from the classic theory of sets, where a strict sense of the participation of an object in a set exists, to the application of fuzzy logic is succeeded with the use of the membership function $m_{A,\ell}(x)$, where x is the value of the linguistic variable A and ℓ is the serial number of M functions which describe A. The membership functions can be the triangular, the trapezoid, the Gauss function, etc. The membership functions and the logical rules compose the means of realization of the classic fuzzy logic models, which consist of four elements: the fuzzification, the development of regulation basis, the deduction mechanism and the defuzzification.

Fuzzification is the process through which a non-fuzzy set is converted to a fuzzy set (or through which the fuzziness of the latter merely increases). A linguistic variable is a variable whose arguments are fuzzy numbers and more generally words represented by fuzzy sets. For example, the arguments of the linguistic variable **temperature** may be *low*, *medium* and *high*. We call such arguments *fuzzy values*. Each and every one of them is modeled by its own membership function. The fuzzy values *low*, *medium* and *high* may be modeled as shown in figure 1. In figure 1 three continuous membership functions, $m_{low}(T)$, $m_{medium}(T)$, $m_{high}(T)$ modeling the arguments *low*, *medium* and *high* respectively, are illustrated. Any value of temperature, e.g. 60 ^{0}C has a unique degree of membership to each fuzzy value of **temperature**. In figure 1, for example, temperature 60 ^{0}C is *low* to a degree zero, *medium* to a degree *0.65* and *large* to a degree *0.35*.

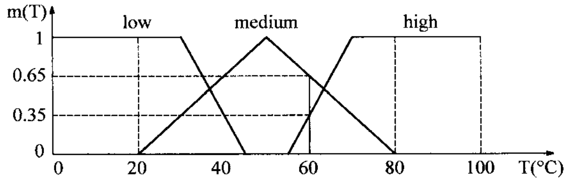

Fig. 1. Membership functions $m_{TEMP}(T)$ describing the primary values low ($\ell = 1$), medium ($\ell = 2$) and high ($\ell = 3$), of the linguistic variable temperature with $M = 3$.

Regulation basis is a set of fuzzy rules describing the dependence of one (or more) linguistic variable to another. These rules are described by the following pattern:

$$\textbf{\textit{If}}\ A_1 \text{ is } x_1\ \textbf{\textit{and}}\ A_2 \text{ is } x_2 \ \ldots\ \textbf{\textit{and}}\ A_N \text{ is } x_N \quad \textbf{\textit{then}}\ B \text{ is } y \qquad (1)$$

where A_1, A_2, … , A_N are the input variables, x_1, x_2, …, x_N are the respective fuzzy values of the input variables, B is the output variable and y is the fuzzy value of the output. For each one of the A_1, A_2,…, A_N and B the respective fuzzy values are described by appropriate membership functions.

The deduction mechanism comprises three sequential steps:

a. The *Larsen-Max Product Implication,* which for every rule of one input-one output implies the membership function from the input to the output.

b. The *degree of fulfillment* (DOF), which is the procedure implying the *Larsen-Max Product Implication* for more than one input variables for each rule. For the k-th vector $x_{1k}, x_{2k},\ldots, x_{Nk}$ the g-th rule is determined:

$$dof_g = m_{A_1,\ell_{1,g}}(x_{1k}) \cdot m_{A_2,\ell_{2,g}}(x_{2k}) \cdots m_{A_N,\ell_{N,g}}(x_{Nk}) \quad (2)$$

c. The *border method*, which forms the final function of output variable, resulting from the set of rules, which were build by the input variables.

Finally, the defuzzification procedure is an equivalence from the space of fuzzy values to a space of non-fuzzy values. Unfortunately, there is no systematic procedure regarding the selection of defuzzification strategies. The most common ones are: the maximum, the mean value of the maximum and the center of the area criterions. When the DOF method is used [15], the most suitable of the above is the criterion of the center of the area (COA):

$$\tilde{b}_o = \sum_{j=1}^{n} m_B(w_j) \cdot w_j \bigg/ \sum_{j=1}^{n} m_B(w_j) \qquad (3)$$

where $\tilde{b}_o$ is the center , n is the number of intervals of width dw, dividing the axis of the output variables, m_B is the membership function of the variable B, w_j is the value for which the membership function becomes $m_B(w_j)$. The essence of this method lies in the definition of the center of gravity of the surface, which is formed by the use of the border method, in reference to the $m_B(x)$ axis. The COA method provides mean square error smaller than the maximum method [15].

In the case of the forecasting model $\tilde{b}_O$ is the estimated variable at the time point of the forecast for which the input variables are given. The model's validation is realized through the absolute percentage error *ape* of $\tilde{b}_O$ by the following expression:

$$ape = \left| \frac{b_O - \tilde{b}_O}{b_O} \right| \cdot 100\% \qquad (4)$$

where b_O is the actual value of demanded variable at the same time point.

3 Fuzzy Midterm Forecasting Model

Based on the above principles of fuzzy logic, a model for midterm forecast of the annual energy demand was developed. The basic notion is the model's optimization regarding:

- the finally necessary input variables for use and their forms {subsection 3.4 and 3.1 respectively},
- the number of membership functions and their characteristics {subsection 3.2}.

In figure 2 the basic steps of the model are represented.

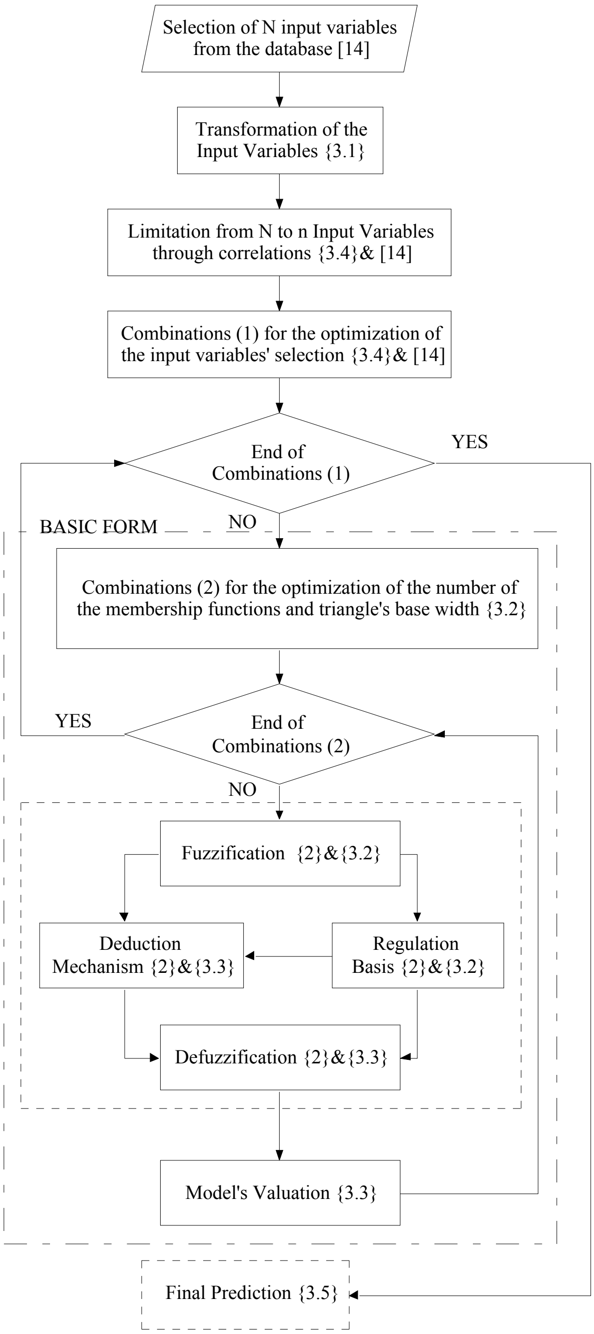

Fig. 2. Basic steps of fuzzy midterm forecasting model

3.1 Transformation of input variables

This model uses as input variables parameters such as number and types of customers, energy consumption, temperatures, and various statistical indices. The actual values of the variables registered in the database are transformed in order to be processed. For values of variables with normal growth the difference of the corresponding variables is used and for exponentially growing values of variables the relative difference. Thus, instead of the value x_{jk} of the *j*-th variable x_j during the *k*-th year, either the difference d_{jk} :

$$d_{jk} = x_{jk} - x_{j(k-1)} \tag{5}$$

or the relative difference:

$$r_{jk} = d_{jk} \big/ x_{j(k-1)} \tag{6}$$

is used and these variables are denoted by p_j with values:

$$p_{jk} = r_{jk} \quad or \quad d_{jk} : k = 1,...,Y \tag{7}$$

where Y is the number of years for which data are available.

The lack of data on certain input attributes of a year can be faced by omitting this year, without breaking the continuity of the values, unlikely with what happens with regression models.

3.2 Fuzzification & regulation basis

The fuzzification is realized by using the triangular membership functions. The odd number of membership functions t to be used and the triangle's base width are to be selected, in order to optimize the performance of the fuzzy forecasting model. The center of the middle triangle c_j of a variable p_j and the initial value of the base width b_{jI} of each triangle, are given by the following expressions:

$$c_j = \sum_{k=1}^{Y} p_{jk} \Big/ Y \tag{8}$$

$$b_{jI} = 2 \cdot \left(\max_{k=1,...,Y} p_{jk} - \min_{k=1,...,Y} p_{jk} \right) \Big/ \left(t_j - 1 \right) \tag{9}$$

where t_j is the number of triangular membership's functions of the variable p_j. Next, the base width of the triangle is modified by ± a % with step *s*%, while the center of the middle triangle remains constant. Thus, the number of possible triangles h, to be examined per variable, equals to:

$$h = 2 \cdot \lceil a/s \rceil + 1 \tag{10}$$

Therefore, if n input variables exist, the total number of combinations to be made is h^n. Following, the fuzzification and the regulation basis are completed for every scenario of the values t_j and b_j for all variables.

3.3 Deduction mechanism & result's validation

Next, all the possible combinations of the rules are classified and the various fuzzy output values for every combination of input rules from the training years are obtained. As a result, the output is better influenced by the total of the fuzzy values obtained during the training, rather than by the fuzzy value that occurs more often. In order to achieve this, the model uses a process involving weights. Assuming that for each fuzzy output value of the model there is a corresponding weight, the price –2 is used for the value 'Very Negative', the price –1 is used for the value 'NEgative', the price 0 is used for the value 'ZEro', the price 1 is used for the value 'PoSitive' and the price 2 is used for the value 'Big Positive'. For instance, in a certain rule the output values may develop the following frequencies:

VN(1) NE(3) ZE(2) PS(2) BP(2)

According to the maximum frequency choice the fuzzy value 'NE' should have been chosen as an output, whereas based on the weight process the conclusion is different since:

[1*(-2)+3*(-1)+2*0+2*1+2*2]/[1+3+2+2+2]=0,1

Thus, the model chooses the fuzzy value 'ZE' since the total rule weight approximates the fuzzy value 'ZE'. If a rule does not occur at all, then the fuzzy value 'ZE' is selected as an output. If a rule occurs only once, then two divides the output weight, so that it doesn't affect the forecasting model too much, since a single occurrence of this specific rule implies little credibility. Therefore, for each rule the fuzzy value of the output with the greater significance according to the training, is selected. Next, by taking into consideration the input data regarding the validation year, the model constructs the left part of this year's rules. The validation year is the last year before the one of the forecast, for which data exist. Following, the rules that correspond to the left part of the rules created for the validation year are selected from the regulation basis and their outputs are read. By applying the deduction mechanism and the COA method, the difference between the forecasted amount of energy, which will be required during the validation year and the amount of energy of the former year, is calculated. Of course, the amount of energy $\widetilde{b}_O$, which will be required during the validation year, is calculated as well. Finally, for each combination the absolute percentage error (*ape*) of the forecasted energy $\widetilde{b}_O$ in respect with the real energy b_O that has been actually demanded is found using the equation (4). The *ape* comprises a criterion of comparison amongst the results of the various combinations.

3.4 Optimization of the input variables' selection

In addition to the complexity due to the large number of candidate membership function of each variable, the large number itself of possible variables *N*, obtained through the data mining process [14], poses considerable computational difficulty. In this case, given that it is possible to examine all the combinations of all *N* input variables, the basic form of the fuzzy model would have to be executed 2^N times. So, after taking into account the optimization of the membership function as to the width of the triangle's base, the final combinations to be examined are:

$$combinations = \sum_{v=1}^{N} \binom{N}{v} \cdot h^v : t_j = const, \forall j \quad (12)$$

After having considered that the initial preprocessing through data mining leads to an average of 10 variables, as in [14], it became imperative for the preprocessing to be repeated with a correlation index between input-output and a correlation amongst the input variables, so that the number of combinations decreases. Thus, the correlation index between d_j and *y* is computed. If for a term d_j its correlation index is greater than a pre-specified value cor_1 then this term is retained for further processing; else, it is not considered any further. Next, for the retained terms a cross correlation analysis is performed. If the correlation index between any two terms is smaller than a pre-specified value cor_2 then both terms are retained; else, only the term with the largest correlation with respect to output y is retained while the other is not considered any further. This is how optimization is achieved regarding both the selection of the input variables and the formation of the membership functions. In this way the input variables, which are used by the model, decrease from *N* to *n* and the combinations are also decreased.

3.5 Final prediction

Finally for each one of the possible combinations of the *n* current input variables, the fuzzy value of each input, which corresponds to the data of each training year, is determined. Moreover, the membership functions for all fuzzy variables are defined for each one combination of the numbers of membership functions' variables and their triangle's base widths. As a result, rules are created for each year, whose number varies from 2^0 to 2^n. This process is repeated as many times as needed in order to check all the possible combinations. After this procedure is completed the combination that presents the minimum error in the forecast of the validation year is selected. Then this combination is used for the realization of the forecast regarding the year of interest. The forecast is made in the exact same way it was done for the validation year, only now the combination of base widths and input data is given. The energy needed during the year of the forecast derives from the difference between the forecasted amount concerning the year of the forecast and the amount concerning the validation year.

3.6 Algorithm

In summary the main steps of the proposed energy-forecasting model are the following:

1. The *N* input variables are selected by using data mining from the database [14].
2. The input variables decrease from *N* to *n* through correlation analysis.
3. If it is necessary, the input variables are transformed to their differences or their relative differences.
4. The combinations for the *n* input variables are determined, for each combination the following steps are executed:
   a. For each input variable the number of membership functions and triangle's base width are determined via the corresponding combinations.
   b. The fuzzification of the values of each final form of variables is realized
   c. The rules concerning the years, about which the parameter values are included in the database, are formed.
   d. After classifying all the possible combinations of these rules the fuzzy output value is determined via the weight process. On the grounds of these rules the regulation basis is created.
   e. Using the regulation basis, as well as the deduction mechanism and the COA defuzzification method, a forecast is made concerning the last year about which data exists (validation year).
5. The combination that produces the minimum error of forecast for the validation year is selected and the fuzzy model is realized.
6. The left part of the rule concerning the forecasting year is formed, based on the combination that was selected after the completion of the previous step and the corresponding rule is found out.
7. Finally, the expected amount of energy during the year of the forecast is appreciated, by applying the methods mentioned in step 4e.

4 Case Study

The proposed method is implemented for two types of customers: residential customers and high voltage industries. The values of the variables in the database [14] concern the period 1982 - 2001.

4.1 Forecasting for residential customers

In this case, based on the knowledge and experience of PPC and through the procedure of data mining [14], the following data was selected, with which the model was supplied: annual energy (y), gross national product (x_1), annual energy of previous year (x_2), current year (x_3), heat-days (x_4) and cool-days (x_5) in Athens, heat-days (x_6) and cool-days (x_7) in Thessalonica, mean price of kWh for a typical household (x_8), statistical indices of oil and coal products (x_9) and food products-beverages (x_{10}) and the number of customers (x_{11}).

Above variables were transformed to differences or relative differences, depending on the steepness of their yearly change. For example for the variable gross national product, which increases exponentially, the relative difference was used.

Then, the correlation indices between r_j or d_j and y were evaluated. Among these, the ones whose correlation index is higher than cor_1 (=0.2 in this case) were retained for further processing. Next, the correlation indices between retained terms r_j and $r_{j/}$ (or $d_{j/}$ etc.) were computed. If between any two terms the correlation index had been greater than cor_2 (=0.9), the variable that had the lowest correlation index to y would have been rejected.

Based on the correlation analysis only the following 4 variables were retained: relative difference of gross national product r_1, difference of heat-days d_4 and cool-days d_5 in Athens, difference of oil and coal products d_9. All possible combinations were examined with a =20, step $s=2$, t=3 *or* 5 *or* 7, using as training years the years 1986-1999, and they were validated using the year 2000. The final model includes the variables r_1, d_4 and d_5.

In figure 3, from the set of membership functions concerning the difference of cool-days three cases are presented. One corresponds to the basic form, one corresponds to $a = +20\%$ and one corresponds to $a = -20\%$ for t=5.

In figure 4, the analysis of the Larsen Max-Product, DOF and border methods is presented in the case of a year regarding residential customers.

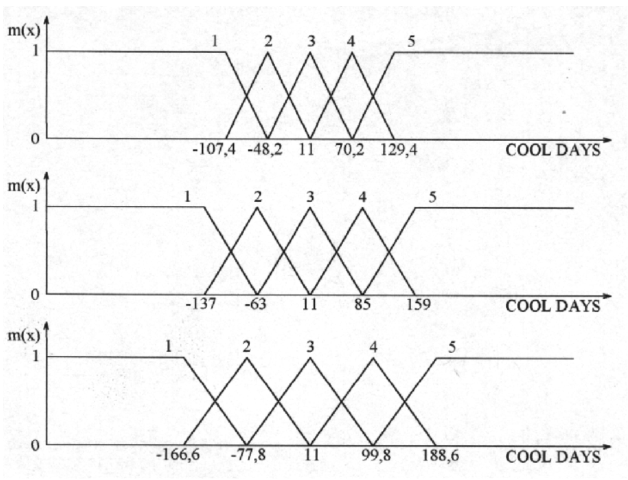

Fig. 3. Example of the membership function's structure regarding the difference of cool-days in Athens for three cases: -20% of base width, basic form, +20% of base width

There are 2^3=8 rules for 3 input variables for $[r_1 \quad d_4 \quad d_5]^T = [8 \quad -16 \quad 4]^T$. The degree of fulfillment for R_1 is:

$$dof_{R_1} = m_{1,2}(r_1 = 8) \cdot m_{4,3}(d_4 = -16) \cdot m_{5,3}(d_5 = 4)$$

$$\Rightarrow dof_{R_1} = 0.5 \cdot 0.8 \cdot 0.9125 = 0.410$$

Rules R_2 to R_7 have output membership function $m_{Energy,3}(d_{energy})$ for the annual difference of energy, as R_1, with smaller *dof* than rule R_1. So output membership function for R_1 covers the respective functions of R_2 to R_7. Rule R_8 has output membership function $m_{Energy,2}(d_{energy})$ with dof_{R8}=0.037. Using the border method the combined form of the membership function is shaped.

In figure 5, the finally input used functions regarding these three variables and the output, are indicated.

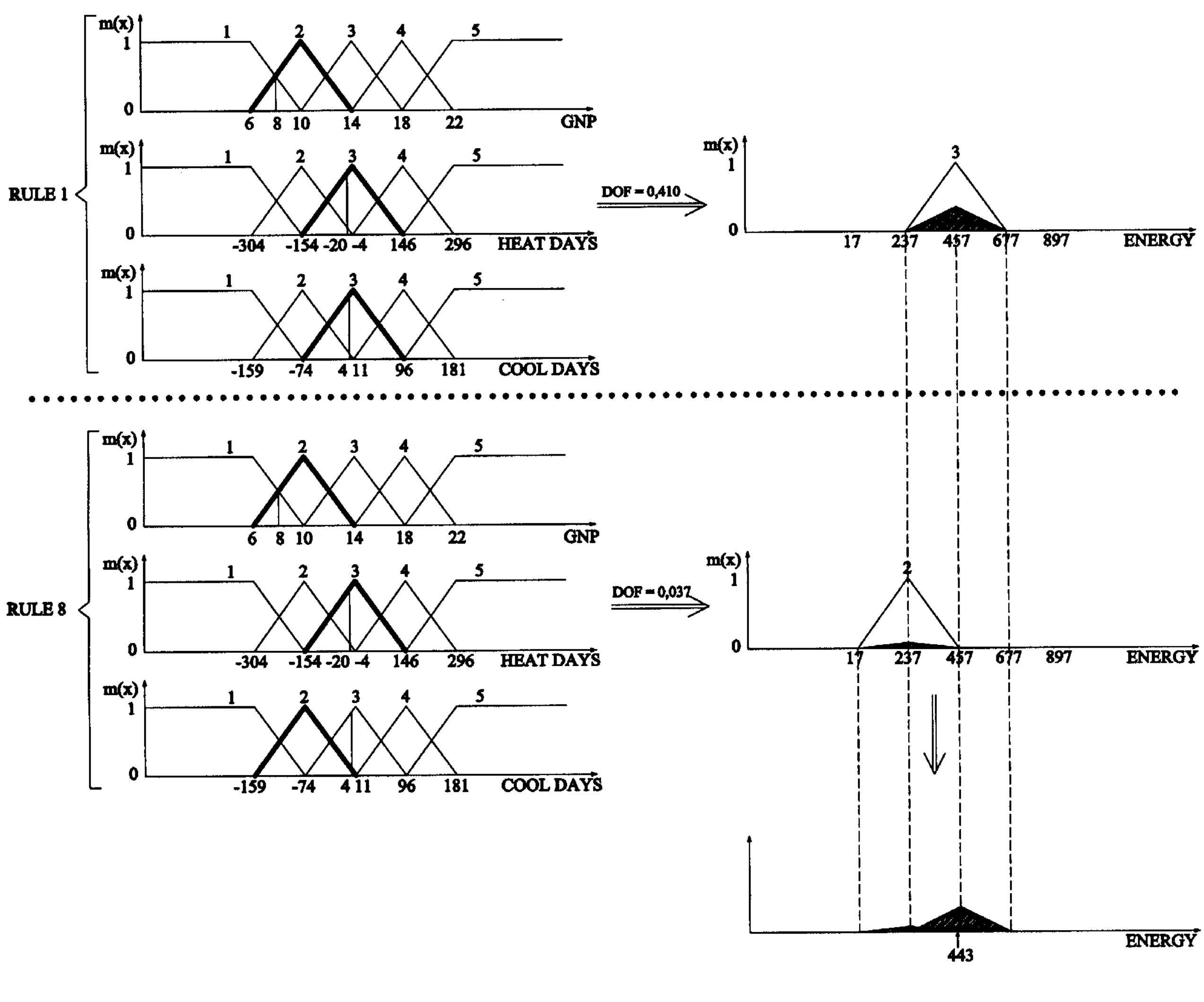

Fig. 4. Example of the application Larsen Max-Product, DOF and border methods is presented in the case of a year regarding residential customers

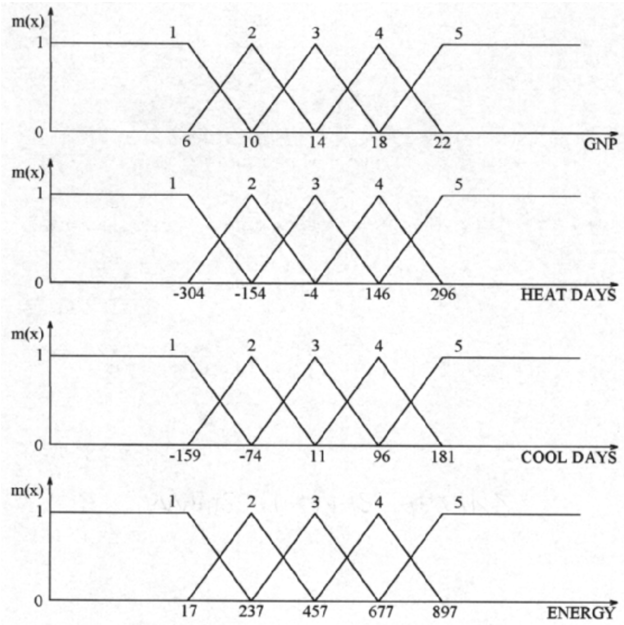

Fig. 5. Membership functions of the three inputs and the energy difference for residential customers

The results of the proposed model were compared to the results of the following previously used forecasting models:

a. A simple regression model expressing the annual energy as linear function of current year.
b. A multiple regression model expressing annual energy as linear combination of gross national product and the annual energy of previous year.
c. The hybrid non-linear multivariable regression model of [14] with a weighting factor equal to 0.81 is supplied by:

$$f_{res} = \begin{cases} c_0 + c_1 \cdot x_3^{1.15} + c_2 \cdot 1/x_3 + c_3 \cdot \exp(-x_{10}) \\ + c_4 \cdot 1/x_4 + c_5 \cdot x_5^{3.5} \end{cases}$$

The results are presented in Table I.

TABLE I
MIDTERM ENERGY FORECAST OF YEAR 2001
FOR RESIDENTIAL CUSTOMERS

Models	Forecasting mean value GWh	Error (%)	Standard Deviation GWh	Training Set/Years	Validation Set/Years
Simple	14255	-2.00	218	1986-'00 15	- 0
Multiple	14284	-1.80	204	1986-'00 15	- 0
Hybrid	14610	0.44	199	1986-'99 14	1998-'00 3
Fuzzy	14650	0.71	-	1986-'99 14	2000 1

Accuracy of the forecasting is given with reference to the actual value of annual energy demand for year 2001, which was 14.546 GWh. The minimum validation error for 2000 is +0.12%. From Table I it is obvious that the hybrid non-linear multivariable regression model of [14] is superior to all of the other three models. However the results of the fuzzy model are quite similar to the last one.

4.2 Forecasting for high voltage industries

In this case the following data was selected: annual energy (y), gross national product (x_1), oil and coal products (x_2), paper and paper products (x_3), chemical products (x_4), rubber and plastic products (x_5), basic metal (x_6), manufacture of basic metal (x_7), electric machines (x_8) and non-metallic minerals (x_9) statistical indices, annual energy of previous year (x_{10}), price of kWh (x_{11}) and current year (x_{12}). At the beginning, the current year is subtracted from the data and differences or relative differences are created. Based on the correlation analysis only the following 4 variables were retained: relative difference of GNP r_1, difference of oil and coal products d_2, difference of chemical products d_4, difference of manufacture of basic metal d_7. Any combination of the above terms forms the basis for a candidate-forecasting model. All combinations were examined with a =20, step s=2, t=3 *or* 5 *or* 7, using as training years the years 1982-1999, and they were validated using the year 2000. The final model includes the variables r_1, d_2 and d_4.

The results of the proposed model were compared to the results of a previously used multiple regression model expressing the annual energy as linear combination of the gross national product and the annual energy of previous year and the hybrid non-linear multivariable regression model of [14] that provides us with a weighting factor equal to 1.0:

$$f_{ind} = c_0 + c_1 \cdot x_1^{0.45} + c_2 \cdot 1/x_7 + c_3 \cdot 1/x_8 + c_4 \cdot \exp(-x_{12})$$

The results of the comparison are summarized in Table II.

TABLE II
MIDTERM ENERGY FORECAST OF YEAR 2001
FOR HIGH VOLTAGE INDUSTRIES

Models	Forecasting mean value GWh	Error (%)	Standard Deviation GWh	Training Set/Years	Validation Set/Years
Multiple	6211	-7.13	194	1982-'00 19	- 0
Hybrid	6822	2.00	274	1982-'99 18	1998-'00 3
Fuzzy	6620	-1.02	-	1982-'99 18	2000 1

Accuracy of the forecasting is given with reference to the actual value of annual energy demand for year 2001, which was 6.688 GWh. The minimum validation error for 2000 is -1.00%. From Table II it is obvious that the proposed fuzzy model gives with respect to the mean value better results than the multiple regression method, which gives an error of 7% and the hybrid non-linear multivariable regression model, which gives an error of 2.00%. Unfortunately the fuzzy model does not provide the standard deviation.

5 Conclusion

In this paper a new method for midterm energy forecasting based on fuzzy logic has been presented. The proposed method performs an extensive search in order to select the appropriate input variables of the model through the correlation indices and their combinations, as well as the appropriate structure of the membership functions of fuzzy model. The results obtained by the implementation of the proposed model for two types of customers: high voltage industries and residential customers are presented. This method was compared to standard regression methods leading to satisfactory results.

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