Building models for forecasting energy consumption using a fuzzy knowledge base and a regression model

D T Muhamediyeva
"Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University, Tashkent, Uzbekistan

E-mail: dilnoz134@rambler.ru

Abstract. The main purpose of the work is to build models for forecasting energy consumption. With the goal in mind, the problems of building energy consumption models are solved using the Sugeno fuzzy knowledge base and the regression model. The presentation of the material is carried out on the example of constructing a fuzzy model of the dependence of energy consumption on the number of population and gross domestic product (GDP). It is necessary to find out how energy consumption depends on the population, GDP, and the price of oil. The synthesized fuzzy model will have one output and three inputs.

1. Introduction
The gross domestic product of Uzbekistan is 57.71 (billion US dollars) in 2020. GDP per capita of Uzbekistan -1,702 USD in 2020.

In terms of gas production, Uzbekistan ranks third among the CIS countries and is among the ten largest gas producing countries in the world (63-65 billion m³ of gas per year) [4]. In recent years, Uzbekistan has produced 53-57 billion cubic meters of gas. Gas consumption in the republic in recent years has amounted to 45-50 billion cubic meters [1-5].

2. Materials and methods
Consider a method for predicting power consumption based on the creation of approximating models. The approximating model is an adaptive neuro-fuzzy network ANFIS. The initial data used for training and checking the network settings are formed on the basis of samples of real data on the energy consumption of the operational information complex [6].

In the example shown here, the forecasting of energy consumption was carried out using neural network technologies.

An object of the form is considered:

\[ y = f(x_1, x_2, ..., x_n) \]  

For which the connection <inputs(x_i)-output( y )> can be represented as an expert knowledge matrix.

Figure 1, shows that the neuro-fuzzy network has five layers:
Figure 1. Structure of a neuro-fuzzy network.

Table 1. Elements of a neuro-fuzzy network.

| Node | Name          | Function                        |
|------|---------------|---------------------------------|
|      | Entrance      | \( \nu = \nu \)               |
|      | Fuzzy term    | \( \nu = \mu^T(\nu) \)         |
|      | Fuzzy rule    | \( \nu = \prod_{i=1}^{L} \nu_i \) |
|      | Rule class    | \( \nu = \sum_{i=1}^{L} \nu_i \) |
|      | Defuzzification | \( \nu = \frac{\sum_{j=1}^{M} \nu_j \bar{d}_j}{\sum_{j=1}^{M} \nu_j} \) |

\( \mu^T(\nu) \) - membership function of the variable \( \nu \) to the term \( T \); \( \bar{d}_j \) - class center \( d_j \in [\nu, \bar{\nu}] \).
\[ w_{jp}(t+1) = w_{jp}(t) - \mu \frac{\partial E_i}{\partial w_{jp}(t)} \] (2)

\[ c_i^{jp}(t+1) = c_i^{jp}(t) - \eta \frac{\partial E_i}{\partial c_i^{jp}(t)} \] (3)

\[ b_i^{jp}(t+1) = b_i^{jp}(t) - \eta \frac{\partial E_i}{\partial b_i^{jp}(t)}, \quad j = 1, m, i = 1, n, p = k_j. \] (4)

Minimizing criterion:

\[ E_i = \frac{1}{2} (y_i - \hat{y}_i)^2 \] (5)

Used in the theory of neural networks, where [11]:

\[ \frac{\partial E_i}{\partial w_{jp}} = \varepsilon_1 \varepsilon_2 \varepsilon_3 \frac{\partial \mu_d^i(y)}{\partial w_{jp}} \] (6)

\[ \frac{\partial E_i}{\partial c_i^{jp}} = \varepsilon_1 \varepsilon_2 \varepsilon_3 \varepsilon_4 \frac{\partial \mu^{jp}(x_i)}{\partial c_i^{jp}} \] (7)

\[ \frac{\partial E_i}{\partial b_i^{jp}} = \varepsilon_1 \varepsilon_2 \varepsilon_3 \varepsilon_4 \frac{\partial \mu^{jp}(x_i)}{\partial b_i^{jp}} \] (8)

Where:

\[ \varepsilon_1 = \frac{\partial E_i}{\partial y} = y_i - \hat{y}_i \] (9)

\[ \varepsilon_2 = \frac{\partial y}{\partial \mu_d^i(y)} = \frac{d_j \sum_{j=1}^{m} \mu^d_j(y) - \sum_{j=1}^{m} d_j \mu^d_j(y)}{\left( \sum_{j=1}^{m} \mu^d_j(y) \right)^2}, \] (10)

\[ \varepsilon_3 = \frac{\partial \mu^d_j(y)}{\partial \left( \prod_{i=1}^{n} \mu^{jp}(x_i) \right)} = w_{jp} \] (11)

\[ \varepsilon_4 = \frac{\partial \left( \prod_{i=1}^{n} \mu^{jp}(x_i) \right)}{\partial \nu^{jp}(x_i)} = \frac{1}{\mu^{jp}(x_i)} \prod_{i=1}^{n} \mu^d_i(x_i). \] (12)
An important task is to determine the inputs of the network. The main independent variables are:

- Retrospective data on actual consumption.
- Meteorological factors (population, price) [10].

3. Results

Suppose that the output variable PE - energy consumption can be influenced by 3 candidate input variables: Nas - population, VVP - GDP and Price - price (figure 2).

![Figure 2. An example of how this search function works.](image)

The subtractive clustering mining method used by the genfis 2 function allows you to quickly extract fuzzy rules from the data. This is a one-pass method that does not use iterative optimization procedures. As a result of the execution of the above command, a fuzzy Sugeno model of the first order is synthesized.

Let's try to improve the model using ANFIS training. Let's set a relatively small number of training iterations - 20. During training, we will use only the training sample, followed by testing the tuned fuzzy model on the testing sample.

4. Discussion

The second method "Multivariate regression analysis" is designed to predict the dynamics of indicators specified in the form of time series for the selected type of regression in the presence of a linear, power or linear-logarithmic correlation.
It is required to solve the following tasks:

- Construct a regression equation.
- To find the predicted values by the resultant attribute by setting the expertly estimated values for all the argument attributes on the forecasting horizon.

The system calculates the pair correlation coefficient, which is determined solely by the source data. The pairwise correlation coefficient $r_{xy}$ can have a plus or minus sign. Its positive value indicates a direct connection. The closer $r_{xy}$ is to one, the closer the relationship. Its negative value indicates feedback; in this case, the boundary is -1. If $r_{xy}$ is equal to 1, then this indicates that the relationship between the features is functional, i.e. the factor attribute completely determines the values of the resultant one. When $r_{xy}$ is close to zero, the relationship between $x$ and $y$ is weak (figure 3).

![Graph of dependence of fuzzy modeling errors on the number of training iterations.](image)

**Figure 3.** Graphs of dependence of fuzzy modeling errors on the number of training iterations.

The system automatically calculates and analyzes the correlation matrix. Significant values of paired correlation coefficients indicate the possibility of a significant relationship between the correlated indicators.

The coefficients of the equation of multiple linear regression on a natural scale show how much the value of the resulting parameter will change with a change in the values of each factor by 1% with fixed values of the remaining factors-arguments.

The coefficients of the multiple regression equation on a standardized scale show by what part of the standard deviation the dependent variable will change if the values of each of the argument factors change by the full value of their standard deviation with fixed values of the other factors.

The obtained estimates of the effective parameter can be used as predictive ones. To generate fuzzy knowledge bases and training samples, reference models "five inputs - one output" were used.

Graphs of these dependencies are shown in figure 4.
5. Conclusion
As a result of the study, a method was proposed for forecasting energy consumption, based on the construction of approximating models on samples of real data for seven countries in transition. Based on the proposed method, an approximating forecast model was created using two methods for identifying a nonlinear dependence - using the Sugeno fuzzy knowledge base and a regression model. The forecast error for the first model was 0.18-7.77%, and for the second model 1.5-79.5%.

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