ENERGY TIME SERIES – FUZZY LOGIC PREDICTION

Abstract: *The article describes the design of the calculation method of heat supply diagram prediction by means of fuzzy logic. Other methods such as Box-Jenkins methodology and the use of artificial neural networks are mentioned here for the purpose of comparing their prediction abilities in energy time series. The use of fuzzy logic seems very successful in the prediction of energy time series.*

1. Introduction

There are manifold methods used for the predictions of time series. In addition to the classical method such as Box-Jenkins methodology, we can use artificial neural networks, genetic algorithms or fuzzy logic. See articles 1,2,3,4,5,6. This article describes the search for suitable type of fuzzy regulator for the purposes of prediction of time series.

2. Description of fuzzy regulator

Fuzzy set A is defined in terms (U, μ_A), where U is relevant universal set and μ_A: U $\rightarrow \langle 0,1\rangle$ 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 μ_A(x). We call $\boldsymbol{F}$(U) the set of all fuzzy set. Then „classical" set A is fuzzy set where: μ_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 regulator: One of the possible applications is a 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: $\boldsymbol{E_i} = (E_i, \boldsymbol{T}(E_i), E_i, G, M)$, $i = 1,..., n$.
Output variables: $\boldsymbol{U} = (U, \boldsymbol{T}(U), U, G, M)$.
We consider the fuzzy regulator as the statement of the type: $\mathfrak{R} = \mathfrak{R}_1$ else $\mathfrak{R}_2$ else ,..., else $\mathfrak{R}_p$,
where $\mathfrak{R}_k$ is in the form: $\mathfrak{R}_k$ = **if** e_1 **is** $X_{E_1,k}$ **and** e_2 **is** $X_{E_2,k}$ **and** ..... **and** e_n **is** $X_{E_n,k}$ **then** u **is** $Y_{U,k}$,
where $e_1\in E_1$,..., $e_n\in E_n$, $u\in U$, $X_{E_i,k} \in \boldsymbol{T}(E_i)$, $Y_{U,k} \in \boldsymbol{T}(U)$ for $\forall i$= 1,...,n, for $\forall k$=1,.., p.
We mark meaning of the mathematical statement $\mathfrak{R}$ by M($\mathfrak{R}$)=$\boldsymbol{R}$. M($\mathfrak{R}$) and the fuzzy relation on $E_1\times E_2\times...\times E_n\times U$ is defined by $\boldsymbol{R}$=M($\mathfrak{R}$)=$\bigcup_{k=1}^{p}$ M($\mathfrak{R}_k$), where else it is considered as an union and M($\mathfrak{R}_k$) is defined in the form: M($\mathfrak{R}_k$) = $A_{E_1,k} \times A_{E_2,k} \times...\times A_{E_n,k} \times A_{U,k}$. 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,…, n and $A_{U,k}$ = M($Y_{U,k}$) is the fuzzy set on universal U for $\forall k$=1,…, p.
Let a_{E_i} i=1,…,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 = ($a_{E_1} \times a_{E_2} \times...\times a_{E_n}$)°$\boldsymbol{R}$. 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 $\boldsymbol{R}$ 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 fuzzy regulator defined in such a way is called **Mamdami** fuzzy regulator.
When we searched for the suitable fuzzy regulator we found **Sugeno** one. Fuzzy regulator Sugeno has the input linguistics variables similar to the fuzzy regulator Mamdani, but all the input variables have the same number of linguistics values (j = 1, 2, …, k) and output values are in linear form:

$$Z_j = \alpha_j + \beta_{1,j} \text{ defuzz}(a_{E_1})+\beta_{2,j} \text{ defuzz}(a_{E_2}) + \ldots+ \beta_{n,j} \text{ defuzz}(a_{E_n}),$$

where α_j, $\beta_{i,j}$ i= 1, 2, …, n, j = 1, 2, …, k are suitable constants.

3. The search of suitable type of fuzzy regulator for the purposes of prediction of time series analyses

The Sugeno fuzzy regulator is designed in such a way as to give one output with n inputs. The inputs of regulator are represented by the values of time series preceding the value that we want to predict. The output value is prediction value. The fuzzy regulator gives us only one prediction value therefore we repeat the calculation until the prediction value is considered as required a real value for the next calculation. By repetition of the process 48 times we receive 48 prediction values.

The long-term testing shows that the quality of prediction is given by the set of number of members of time series which creates the input of fuzzy regulator. The prediction of time series by means of fuzzy regulator does not describe the course of time series when the number of members is either low or high (the low or high sensitivity of regulator). See fig. 1, 2, 3, 4, 5, 6.

The fuzzy regulator has been tuned to the initial part of time series to set the number of input values (the number of input values of time series). The cluster method has been used for the purposes of assigning members of time series to clusters. The number of clusters define the number of input linguistics value of input linguistics variable. We choose the output of Sugemo regulator in the form of linear dependence $Z_j = \alpha_j + \beta_{1,j}\ \mathrm{defuzz}(a_{E_1}) + \beta_{2,j}\ \mathrm{defuzz}(a_{E_2}) + \ldots + \beta_{n,j}\mathrm{defuzz}(a_{E_n})$. We found the constants α_j, $\beta_{i,j}$ $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, k$ (where n is number of linguistics variable and m is number of input linguistics value) by the optimization methods. The design and tuning of fuzzy regulator Sugeno has been made in the programme **Matlab 5.3 – FuzzyTolbox**.

The examples of dependence of the number of input variables for prediction:

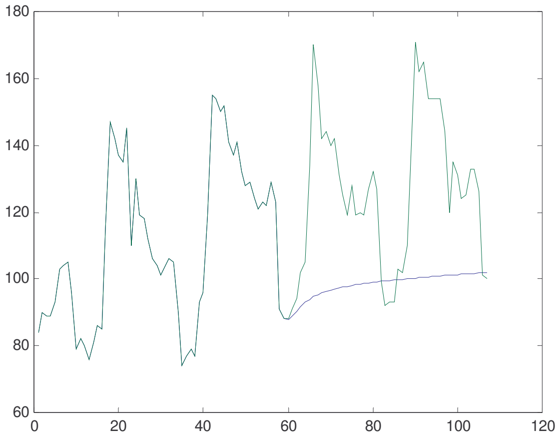


Fig. 1. 2 input variables, 3 input values

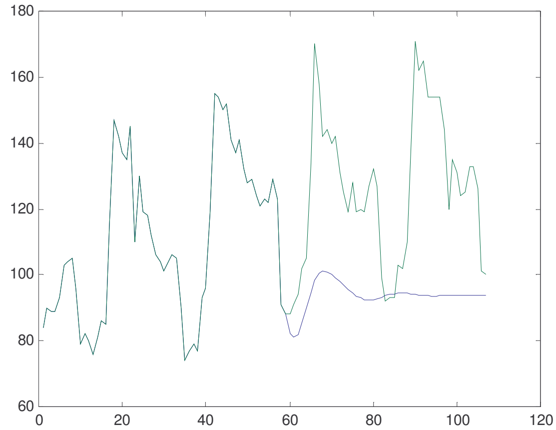


Fig. 2. 4 input variables, 4 input values

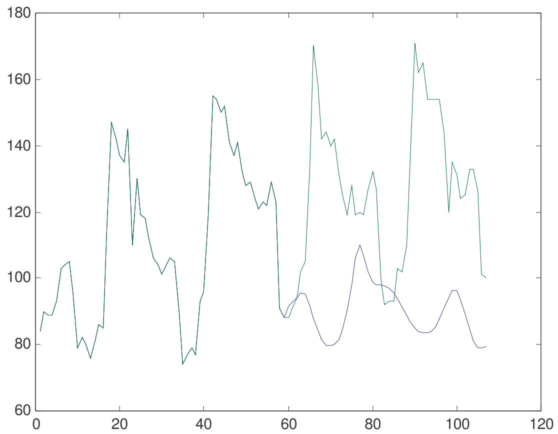


Fig. 3. 6 input variables, 5 input values

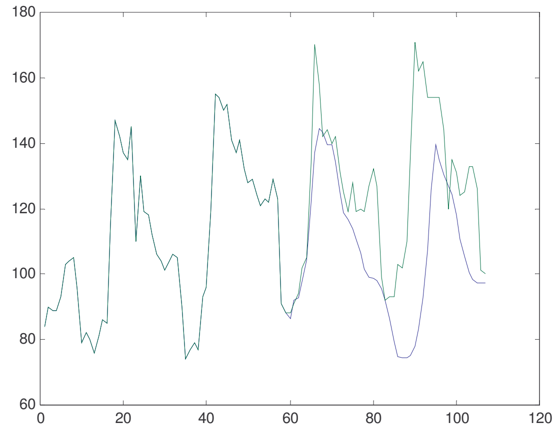


Fig. 4. 8 input variables, 8 input values

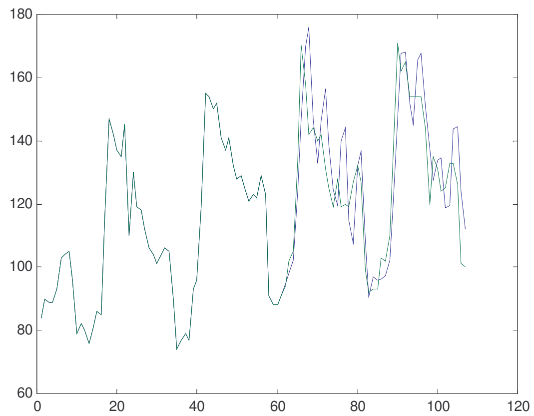


Fig. 5. 11 input variables, 14 input values

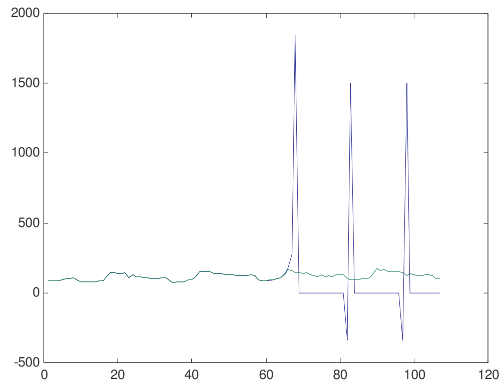


Fig. 6. 13 input variables, 23 input values

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

$$\text{MAPE} = \frac{1}{k}\left(\sum_{i=1}^{k}(\text{abs}(P_i - R_i)/R_i)\right).$$

4. Example 1. – Time series of heat consumption of the town of Brno

The first case which has been tested was the time series of heat consumption of the city of Brno in MW measured from 01:00 06.02.1978 to 01:00 25.2.78 within the following two days (hourly sampling, 408+48 values). The test has been made on the time series used in articles 1,2,3,4 for the purpose of comparing the results of prediction. The graph of time series is on the Fig.7.

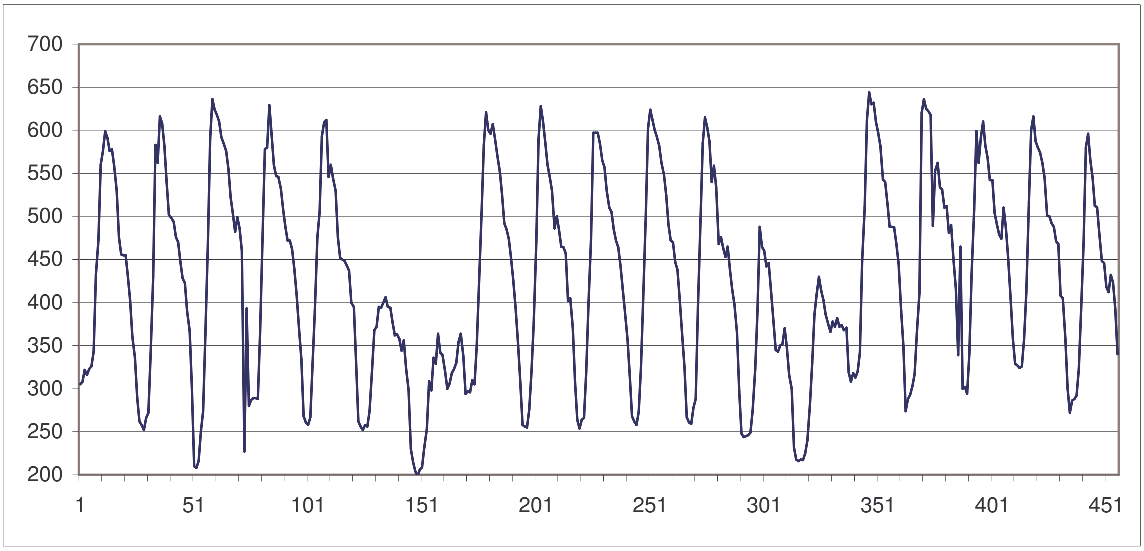


Fig.7. The town of Brno – heat consumption

The suitable fuzzy regulator Sugeno is represented by 4 input variables and 7 input values for the purposes of prediction of time series of heat consumption of the town of Brno. See fig. 8, 9.

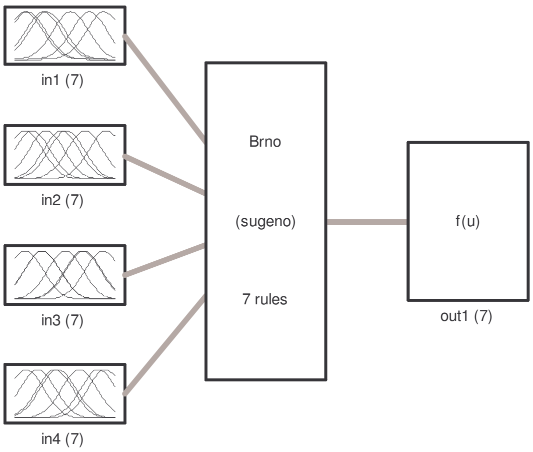


Fig. 8. 11. Sugeno regulator of the town of Brno

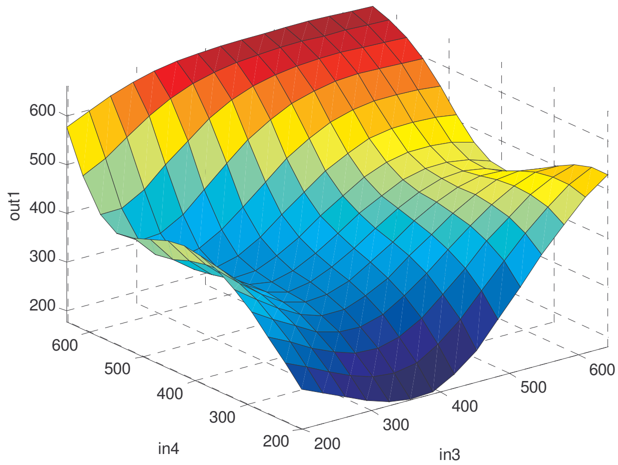


Fig. 9. The part of regulation surface

The best prediction has been accomplished by means of fuzzy logic where MAPE = 0.082. A little worse was the prediction made by artificial neural network where MAPE = 0.096 and the biggest prediction error was calculated by means of Box-Jenkins methodology where MAPE = 0.106. See fig. 10. The prediction by means of genetic algorithm only enables trend prediction and therefore it was not evaluated. This method is used only for the support of decision making process.

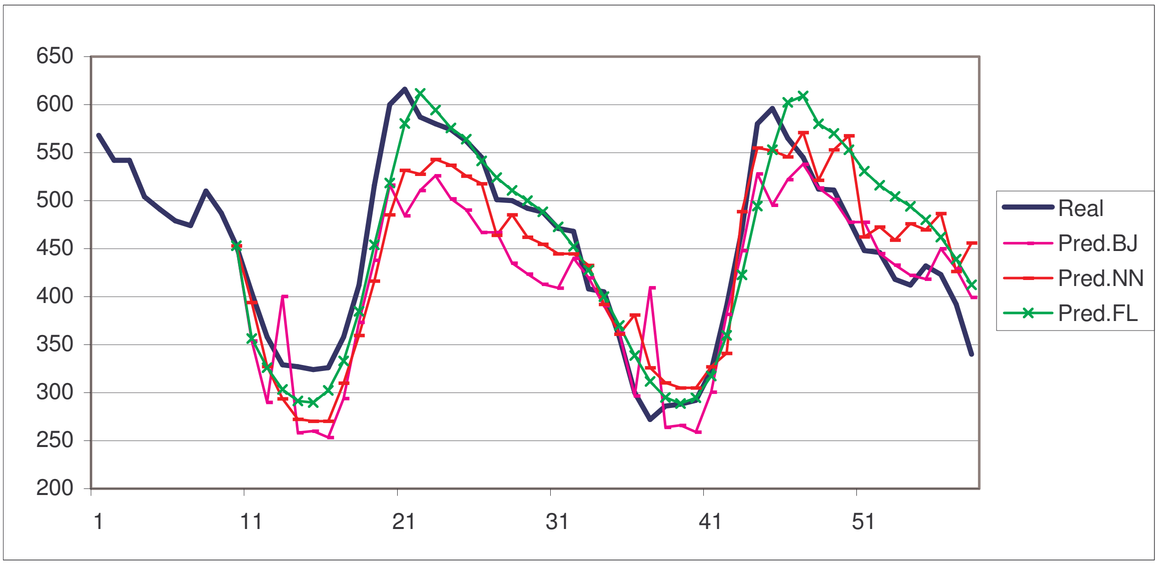
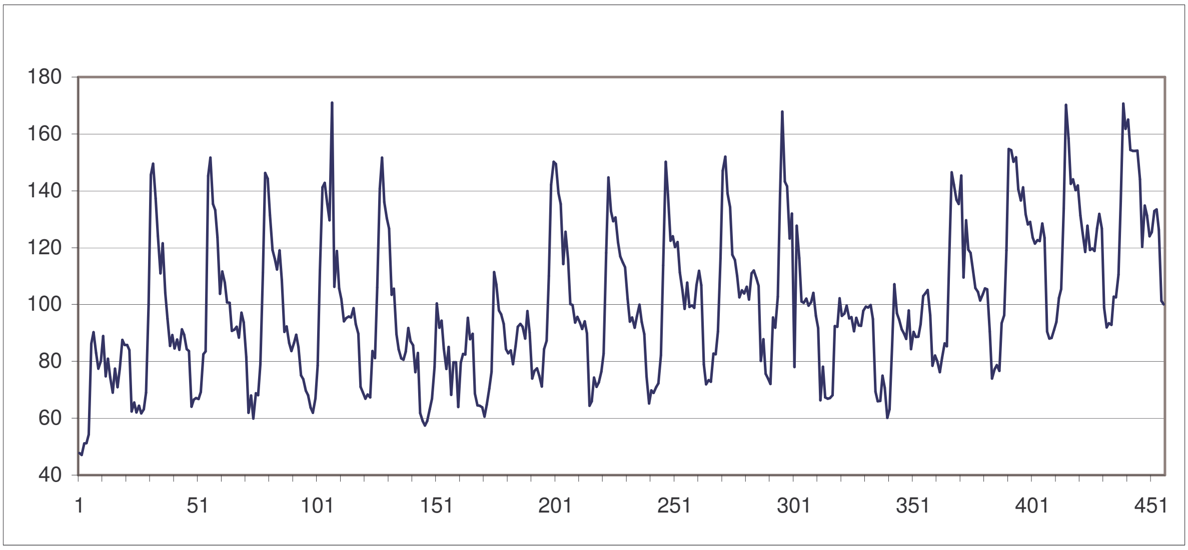


Fig. 10. The town of Brno – heat consumption - prediction

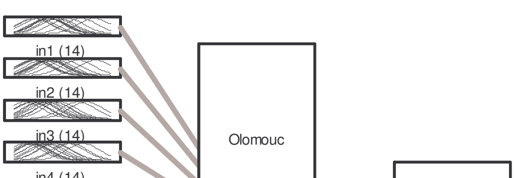
5. Example 2. – Time series of consumption of heat of town Olomouce

The second case which has been tested was the time series of heat consumption of the town of Olomouc in MW measured from 01:00 01.112.1998 to 01:00 20.11.98 within the following two days (hourly sampling, 408+48 values. The test was made on the time series used in articles 5 for the purpose of comparing the results of prediction. The graph of time series is on the Fig.11.



Obr.11. The town of Olomouc – heat consumption

The suitable fuzzy regulator Sugeno is represented by 11 input variables and 14 input values for the purposes of prediction of time series of heat consumption of the town of Olomouc. The reason for the greater number of input variables is given by complicated course of time series. See fig. 12, 13.



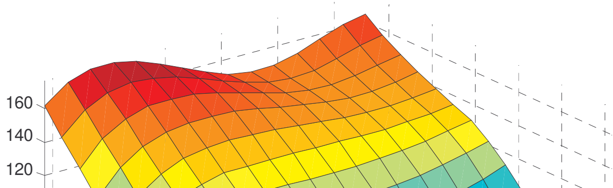


Fig. 12. 11. Sugeno regulator of the town of Olomouc

Fig. 13. The part of regulation surface

The best prediction has been made by means of fuzzy logic where MAPE = 0.078. A little worse was the prediction made by means of Box-Jenkins methodology where MAPE = 0.090 and the biggest prediction error was made by the artificial neural network where MAPE = 0.169. See figure 14.

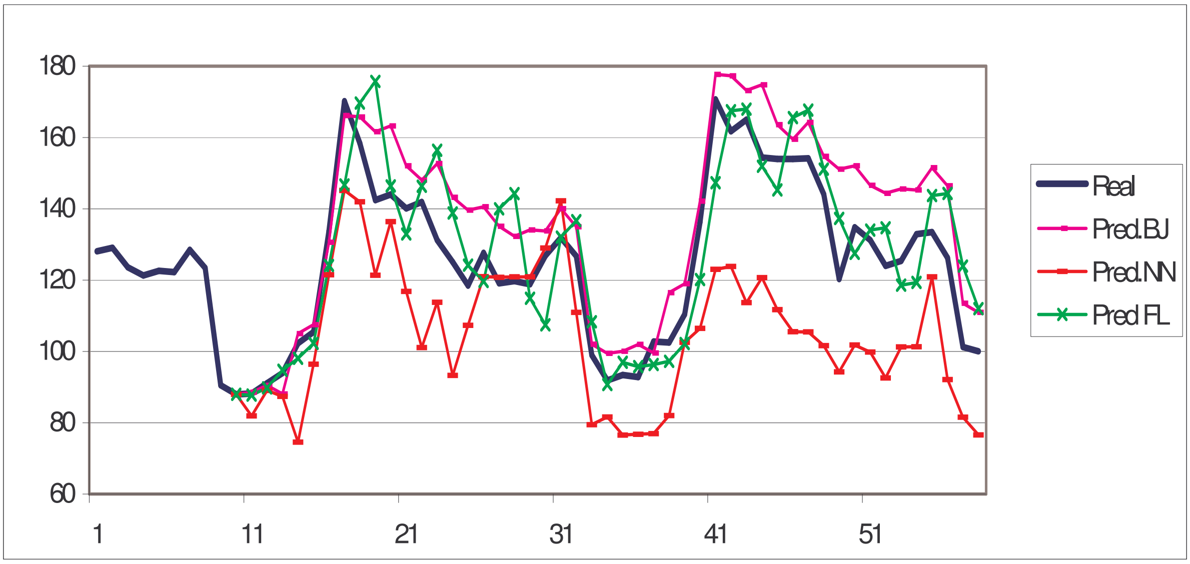


Fig. 14. The town of Olomouc - heat consumption - prediction

6. Conclusion

The paper describes the design of the calculation method of heat supply diagram prediction by means of fuzzy logic. Other methods such as Box-Jenkins methodology and the use of artificial neural networks are mentioned here for the purpose of comparing their prediction abilities of energy time series. The use of fuzzy logic seems very successful in the prediction of energy time series. The prediction errors MAPE point to quality prediction in both tested cases. The problem of different consumption of heat during the working days and weekends can be solved by the so called superposition of models designed formerly and described in articles 1, 2.

The aim of prediction is to improve the quality of the control of the technological process – the heat energy production in the systems of centralized heat supply and, thus, save fuel, energy and environment.