ELECTRIC ENERGY CONSUMPTION FORECAST WITHIN THE WASTEWATER TREATMENT PLANT ORADEA

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ABSTRACT
This paper focuses over short term load forecast (STLF) at wastewater treatment plant Oradea which is an important consumer of electricity from the national energy system. The method used for forecasting and database analysis is to examine the statistical database containing the values of power measurements and analyse the correlation between them and performing forecast by a classical method (linear regression - LR) and forecast using dynamic method (artificial neural networks - ANN). Conclusions will be drawn on the basis of research results.

Keywords: electric energy consumption influence factors, wastewater treatment plant efficiency, correlation between the influence factors and the electric energy consumption

INTRODUCTION
In wastewater treatment plants is very difficult to manage the electric energy consumption influence factors because the process is continuous. On one hand the sewage treatment station process is continuous, wastewater drains from the sewage system, and on the other hand, technology is based on unitary processes (physical, chemical and especially biological) that cannot be stopped or disconnected from the power supply.

MATERIALS AND METHODS
A prerequisite for developing an accurate forecasting model is thorough understanding of the consumption patterns to be modelled [1-3]. This knowledge about the behaviour of the load is learned from experience with the use of consumer data and statistical analysis of consumption in the past. Electricity consumers operating in a similar economic environment and climate are usually similar consumers, behaviour and consumption forecast models developed for one consumer can easily be adapted for use at another consumer [4, 5]. Load supplied by a power distribution system (EE) has a dynamic development and reflects directly the activities and conditions in the environment [6].

The treatment plant receives wastewater from Oradea and the neighbouring villages and it is connected to the two main collectors: 70/105 cm ovoid and 165/260 cm bell. Wastewaters from lower areas of the city are sewed in the 10 pumping stations, from where they are pumped to gravity sewers. Upstream to the treatment plant there is a compensation pool that is used when flow during heavy rains. To compensate for lack of capacity (Q> 2200 l/ s) and prevention of accidental pollution, downstream to the treatment plant is a biological ~ 50 ha ponds, where water is discharged into the river Crişul Repede in a controlled and approved by competent authorities way.

Treatment plant is mechanical-biological type, and purifies the domestic and industrial wastewater from Oradea and some adjacent areas, the effluent being discharged to emissary Crişul Repede, 10 km upstream from the point of crossing the border with Hungary.
The power network must be fed from at least two supply lines - independent medium voltage lines (fed from different power stations) which to be equipped with automatic operate reserve. Four independent power lines fed wastewater treatment plant Oradea.

Oradea treatment plant is connected to the public through four 20kV electricity supply lines with a maximum allocated capacity of 3.2 MW. In case of power supply loss wastewater treatment plant Oradea can use two cogeneration units of 2x360KW.

There are two transformer station and connection station that are designed to supply electricity to all equipment from the treatment plant. The electricity distribution is made, on spot, from two separate points.

1. Data base presentation

For graphical representation of electricity consumption over a year, clustering was performed to the hourly average power values over a week for one year. This database, of the 8761 hourly average values of powers, was established by recording the consumption of EE during [Thursday, 01/01/2009 ÷ Thursday, 31/01/2010]. This representation allows easy viewing of consumption fluctuations and the allocation of these fluctuations influence of external factors.

Fig. 1. PT1 and PT2 electrical single line diagram

Fig. 2. 3D graphical representation of the electric energy consumption
Fig. 3. 3D graphical representation of the electric energy consumption over a winter month

Fig. 4. 3D graphical representation of the electric energy consumption over a summer month

Fig. 5. 3D graphical representation of the electric energy consumption over a spring month
2. The mathematical model used

In order to rank the factors that influence electricity consumption, we use the standard correlation coefficient to determine the correlation between the values of the database containing hourly average power and the numerical values of the influence factors.
The model used for correlation is given by the equation 1:

\[ r = \text{Correl}(x, y) = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \sum(y - \bar{y})^2}} \]  

(1)

where: \( x \) and \( y \) are the average values of the two data base to correlate.

The mathematical model used is an application of artificial neural network (ANN) multilevel (feed forward) by the method of gradient descent (back propagation) by minimizing an error function which is not a euclidian type [12-14]. Multilevel feed forward networks are trained by supervised methods, which involve the use of training instances of the form: \((X^p, t^p)\), where: \(X^p = (X^p_1, X^p_2, \ldots, X^p_N)\) is the input vector for the training \(p\); 
\(t^p = (t^p_1, t^p_2, \ldots, t^p_M)\) is the vector of desired outputs for \(p\); 
\(N\) is the number of input units of the network; 
\(M\) is the number of output units.

Considering \(F(X)\) the function associated to the processing of the problem, according to the input \(X\), then:

\[ t^p = F(X^p) \]  

(2)

The output obtained by processing the input data using neural network is denoted by:

\[ O^p = (O^p_1, O^p_2, \ldots, O^p_M) \]  

(3)

\(O^p\) can be considered as the result of processing of the input, \(X^p\), by using the function \(F_w(w;X^p)\), based network implemented as an approximation of \(F(X)\). Therefore:

\[ O^p = F_w(w;X^p) \]  

(4)

Recorded error at the processing in the network of the input vector \(X^p\), the measured error in a unit of output \(U_j\) and denoted by \(e^p_j\) is expressed as the difference between desired and actual output achieved, namely:

\[ e^p_j = t^p_j - O^p_j \]  

(5)

The \(E^p\) error, recorded at the processing trough the network of the input vector \(X^p\) and set the whole neural network is obtained by combining the error \(e^p_j\), based on a relationship of the form:

\[ E^p = \sum_{j=1}^{M} f(e^p_j) \]  

(6)

For error calculation we will use the error \(E^p\) and the Zero Based Log-Sigmoid Function:

\[ f(x) = \frac{e^{ax+b}}{1+e^{ax+b}} \]  

(7)

The mathematical model used for classic forecast, linear regression(LR) is:

\[ a + bx \]  

(8)

where:

\[ a = y - bx \]  

(9)

and :
where: $x$ and $y$ are the averages of the known database.

To identify the performance level of the application we will use the mean absolute percentage of errors (MAPE) and root mean squared error (RMSE).

$$MAPE = 100 \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

where:
- $n$ – total number of the forecast values;
- $y$ – real value;
- $\hat{y}$ – forecast value.

Performance of the forecasting process is presented in tables and graphs, exemplifying the forecast results for each consumer analysed. To analyse the results, we specify that, according to ANRE [4, 5] the maximum legal allowable communicated forecast error, equals 25%. In this paper we start from the premise that an acceptable forecast would be below 5%.

**RESULTS**

Forecast parameters of ANN used in each training / forecast are:
- Limit of the learning cycles (epochs) -10000
- Minimum weighting value delta - 0.0001
- Initial weight – 0,3
- Learning rate – 0,3
- Momentum – 0,6
- Neurons in hidden layer – 0
- Activation function – logistic sigmoid with 0 based (unipolar sigmoid)

Forecast for Oradea wastewater treatment plant consumer is highlighted by hourly load curve presented in Fig. 8 and specific elements of characterization, given in Table 2 for ANN forecast, and Fig. 9 and Table 3 for linear regression.
Fig. 8. One week ahead hourly forecast using ANN

Table 2. One week ahead forecast accuracy using ANN

<table>
<thead>
<tr>
<th>Date</th>
<th>MAPE[%]</th>
<th>RMSE[kW]</th>
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<tbody>
<tr>
<td>24.11.2009</td>
<td>9.068601468</td>
<td>18.31756</td>
</tr>
<tr>
<td>25.11.2009</td>
<td>6.259542428</td>
<td>13.28255</td>
</tr>
<tr>
<td>26.11.2009</td>
<td>13.54105533</td>
<td>24.71634</td>
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<tr>
<td>27.11.2009</td>
<td>10.14805153</td>
<td>15.22776</td>
</tr>
<tr>
<td>28.11.2009</td>
<td>6.24559867</td>
<td>11.27394</td>
</tr>
<tr>
<td>29.11.2009</td>
<td>32.24997462</td>
<td>41.82752</td>
</tr>
<tr>
<td>30.11.2009</td>
<td>22.20000361</td>
<td>36.48489</td>
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</tbody>
</table>

Fig. 9. One week ahead hourly forecast using LR

Table 3. One week ahead forecast accuracy using LR

<table>
<thead>
<tr>
<th>Date</th>
<th>MAPE[%]</th>
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<tbody>
<tr>
<td>24.11.2009</td>
<td>3.773530225</td>
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<td>25.11.2009</td>
<td>5.129193265</td>
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<td>6.518388709</td>
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<td>18.62068047</td>
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<td>30.11.2009</td>
<td>23.28087829</td>
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<table>
<thead>
<tr>
<th>MAPE[%]</th>
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<tr>
<td>14.24468967</td>
<td>23.01865</td>
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<tr>
<td>11.11638161</td>
<td>23.18284</td>
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CONCLUSIONS
After the database analysis we can conclude the following:

Figure 2 shows three-dimensional representation of fluctuating electricity consumption, targeted specifically at consumers. It can be seen in Figure 3 level fluctuations of very low electricity consumption, mainly due to very low temperature and the dry period analysed.

In Figure 4 we observe fluctuations due to the alternations of periods of heavy rainfall, and warm and dry periods in a limited time and the lack of use of biogas for heat conversion. Figure 5 shows the increase in electricity consumption, due to the rainy week with sharp increases in temperature, causing melting of snow, causing a larger flow of wastewater to be treated. The correlation coefficient shows very few similarities between days per week, which means consumer trends are dictated by the value of sewage flow. Forecasting electricity consumption using conventional methods (linear regression), led to obtaining values for the indicators that characterize the accuracy of forecasts, namely: MAPE = 11.11% and RMSE = 23.18 kW. Forecast shows a linear regression estimator with accuracy better than the RNA forecast, 11.11% to 14.24%. MAPE significant share of this value have 13.32% on Wednesday, Saturday and Sunday 18.62%, 23.28%. Other days presented acceptable values ranging from 3.77% MAPE for Monday and 7.16% for Thursday. Forecasting electricity consumption using artificial neural networks (ANN), led to obtaining values for the indicators that characterize the accuracy of forecasts, namely: MAPE = 14.24% and RMSE = 23.01 kW.

The database has an acceptable number of hourly average power measurements 8761, RNA processed the learning slow, 2913 epochs, ended by the user, MAPE has a high value of 14.24%. Errors are not homogeneously distributed throughout the week, with high values for Sundays and Saturdays 22.20% and 32.24%, other days having acceptable values, 6.24% and 13.54% Friday and Wednesday. Although best results were obtained using linear regression, forecasting method using artificial neural networks has the advantage of being able to use the consumption influence factors to the extent that there is an accurate database of the values of the influence factor.

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