ELECTRIC ENERGY FORECAST FOR THE INDUSTRIAL CONSUMERS USING NEURAL NETWORK

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Abstract – This paper focuses on short-term forecast of electricity consumption of the industrial consumers using artificial neural networks. The paper is divided into six parts. The first part presents an introduction of the problem analysed. In the second part we present the database containing time series, with hourly average power of the analysed consumers. The following two parts contain a description of the programming environment, and that of the model used. Based on forecasts, conclusions are drawn in the paper.

Keywords: short term load forecast, artificial neural network, industrial consumer, one day ahead load forecast.

1. INTRODUCTION

In the short-term load forecasting (STLF), future consumption is projected by extrapolating a predetermined relationship between load and its influence factors - namely, time and / or weather. Determination of this relationship is a two-step process: (a) identify the relationship between consumption and influencing factors, (b) quantify the relationship by using a suitable parameter estimation technique.

A prerequisite for developing an accurate forecasting model is the understanding of the characteristics of the consumers going to be analysed [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 and climate environment, usually have similar consumer behaviour and consumption forecast models developed for a consumer can usually be easily adapted for use at another consumer [4, 5]. Load supplied by a power distribution system has a dynamic development and reflects directly the activities and conditions in the environment [6].

2. DATABASE PRESENTATION

The database was accomplished by measurements at industrial consumers, in the transformer station serving the users. The database was obtained from the average hourly power measurements in intervals of several days to several years depending of the consumer. Some of the measurements were provided by energetics engineers of industrial entities referred to, some was obtained by measurements performed by the University of Oradea with the professional equipment of the Research Centre "Energy Process Management." Due to confidentiality clauses of the electricity provider and its customers, in some cases, data are composed only of hourly average powers and a summary description of the consumers or of the consumer groups served.

2.1. Industrial consumer C1

Industrial consumer that we will analyse named C1, is an industrial park from the west side of the country, and it consists of a foundry and metal processing specific industries branches. Measurements begin on Tuesday - 01.01.2008 until Wednesday - 31.12.2008.

Measurements were made in the transformer station serving the industrial park. [2]

Elements characterizing the load curve are shown in Fig. 1, 2 and Table 1.
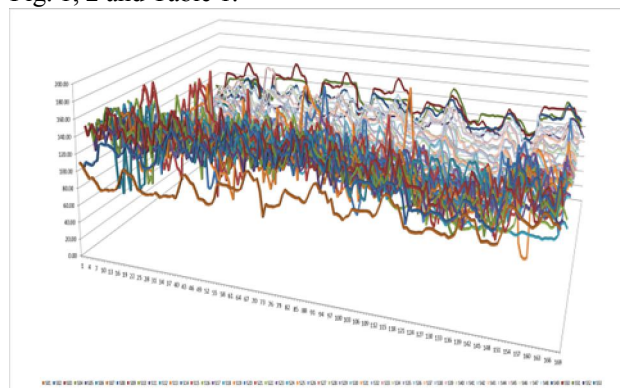

Fig. 1. 3D graphical representation of the hourly load curve in weekly series, throughout the year, for consumer C1 (hourly P_{med} in kW)
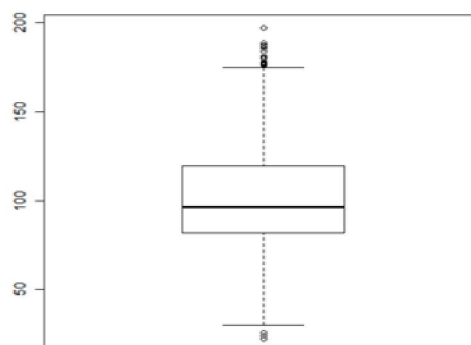

Fig. 2. Box and whisker diagram for consumer C1 (hourly P_{med} in kW)

Table 1 Statistical description of the database C1 (P_{med})

Function	Value [kW]
Minimum(min)	22,15
Maximum(max)	197.34
Median(median)	96,56
Average(mean)	101,3341
Quintiles(quantile)	$q_2 =81,90$
	$q_3 =119,50$
Dispersion(var)	653,7822
Standard deviation(sd)	25,56916

2.2. Industrial consumer C2

The industrial consumer that we will analyse is a sugar factory belonging to SC Zahărul Oradea S.A. . Recordings starts on Monday - 01.01.2007 to Saturday - 31.03.2007. Consumer S.C. Sugar Oradea S.A. (C2) works in two operating modes, production from sugar beet and production from raw sugar. [7]

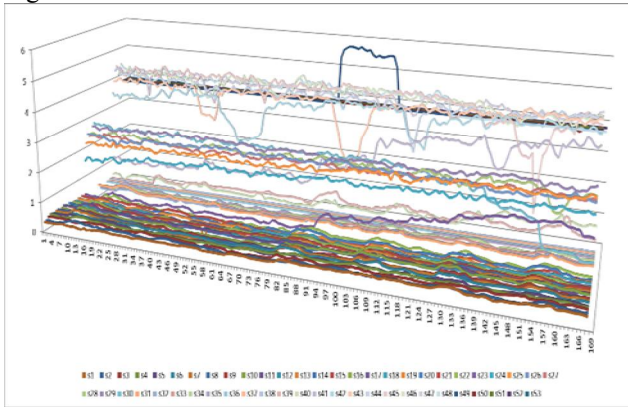Elements characterizing the load curve are shown in Fig. 3 and 4.

Fig. 3. 3D graphical representation of the hourly load curve in weekly series, throughout the year, for consumer C2 (hourly P_{med} in MW)
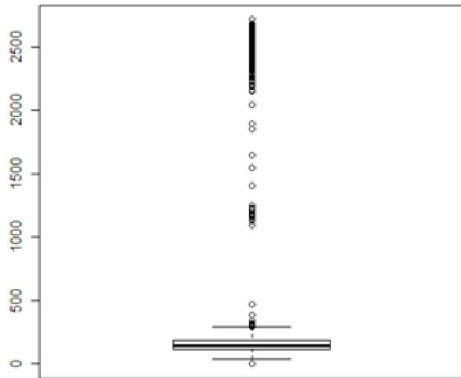

Fig. 4. Box and whisker diagram for consumer C2(hourly P_{med} in kW)

They were found large differences in consumption for the production from sugar beet and the consumption for the production from raw sugar, therefore we consider and analyse the two periods, as belonging to two different customers that we will denote by C2-1, production from raw sugar and C2-2 production from sugar beet. For each load curve, elements of characterization are presented in Fig. 5, 6 and Tables 2, 3.
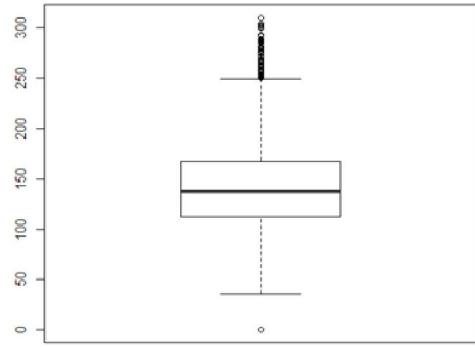

Fig. 5. Box and whisker diagram for consumer C2-1(hourly P_{med} in kW)

Table 2 Statistical description of the database C2-1 (P_{med})

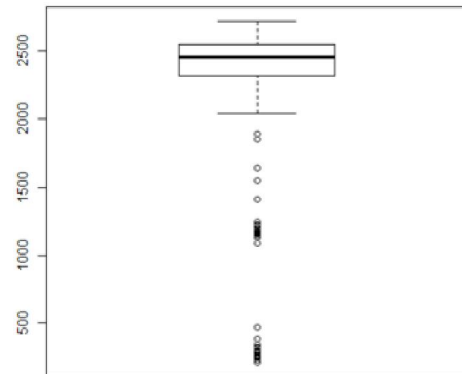| Function	Value[kW]
Minimum(min)	0
Maximum(max)	310.141
Median(median)	137.61
Average(mean)	142.4563
Quintiles(quantile)	$q_2 =112.455$
	$q_3 =167.266$
Dispersion(var)	2629.768
Standard deviation(sd)	51.28126

Fig. 6. Box and whisker diagram for consumer C2-2(hourly P_{med} in kW)

Table 3 Statistical description of the database C2-2(P_{med})

Function	Value[kW]
Minimum(min)	203.399
Maximum(max)	2721.061
Median(median)	2457.899
Average(mean)	2189.4
Quintiles(quantile)	$q_2 =2314.799$
	$q_3 =2548.259$
Dispersion(var)	446808.1
Standard deviation(sd)	668.4371

2.3. Industrial consumer C3

This industrial consumer is a foundry from Oradea belonging to SC Turnătorie Iberica S.A. . Recordings starts on Sunday - 01.02.2009 01:00 to Saturday - 01/31/2010 24:00. Consumer S.C. Turnătorie Iberica S.A. (C3) operates in three shifts, six days a week, with an exception of two weeks in which they worked in two shifts. Given the two periods of interruption of work for 2 weeks and the power audit results[8], the results obtained in this case are presented in Fig. 7, 8 and Table 4.
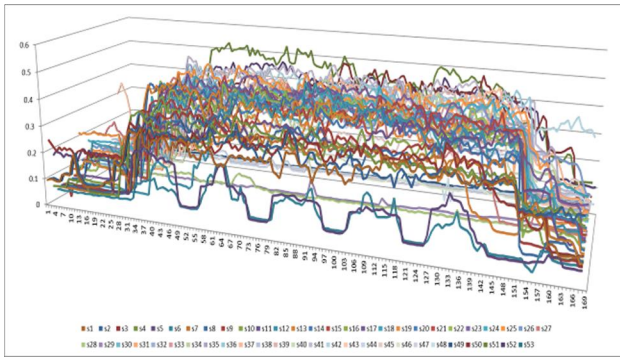
Fig. 7. 3D graphical representation of the hourly load curve in weekly series, throughout the year, for consumer C3 (hourly P_{med} in MW)
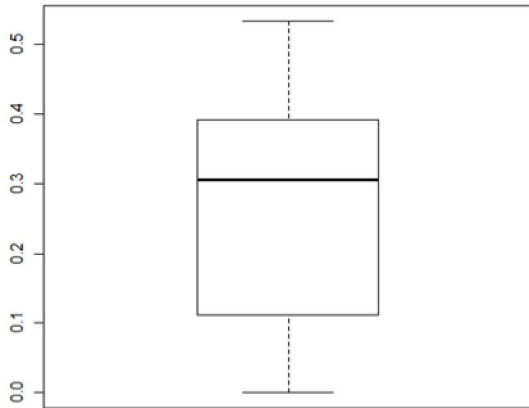

Fig. 8. Box and whisker diagram for consumer C3(hourly P_{med} in MW)

Table 4 Statistical description of the database C3 (P_{med})

Function	Value[MW]
Minimum(min)	0.052954
Maximum(max)	0.534616
Median(median)	0.306
Average(mean)	0.2620182
Quintiles(quantile)	$q_2 = 0.112478$
	$q_3 = 0.392000$
Dispersion(var)	0.02115484
Standard deviation(sd)	0.1454470

3. DESCRIPTION OF THE SOFTWARE ENVIRONMEN AND MATHEMATICAL MODEL FOR THE IMPLEMENTATION OF ARTIFICIAL NEURAL NETWORK (ANN)

3.1. Software environment used

R-Statistics is a language and environment for statistical computing and graphics. It is a project developed by GNU and is similar to the S language and environment and which was developed at Bell Laboratories (formerly AT & T, now Lucent Technologies) by John Chambers and colleagues. R-Statistics offers a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time series analysis, classification, clustering, ...) and graphical techniques, and is very extensible. R-Statistics Language is often the vehicle of choice for research in statistics and R-Statistics provides an open source solution for this.

One of the strengths R-Statistics is the ease with which generate quality graphics, including mathematical symbols and formulas, where necessary. [9]

R-Statistics is available as Free Software under the terms of the Free Software Foundation GNU General Public License in source code form. It compiles and runs on a wide variety of UNIX platforms and similar systems (including FreeBSD and Linux), Windows and MacOS.

The term "environment" is intended to characterize as a fully planned and coherent system, rather than a basic build tools very specific and inflexible, as is frequently the case with other software for data analysis.

R-Statistics is designed around a programming language and allows users to add additional functionality by defining new functions. Much of the system itself is written in programming, making it easy for users to follow the algorithmic choices made. For computationally intensive tasks, the codes C, C + + and Fortran can be added to that link and used at runtime. Advanced users can write C code to manipulate R-Statistics objects directly [10].

3.2. The mathematical model used

The mathematical model used is an application of artificial neural network multilevel (feed forward) by the method of gradient descent (back propagation) by minimizing an error function which is not a euclidian type [11].

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:

$$t^p = F(X^p) \tag{1}$$

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

$$O^p = (O^p_1, O^p_2, \ldots, O^p_M) \tag{2}$$

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:

$$O^p = F_w(w; X^p) \tag{3}$$

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:

$$e^p_j = t^p_j - O^p_j \tag{4}$$

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:

$$E^p = \sum_{j=1}^{M} f(e_j^p) \qquad (5)$$

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

$$f(x) = \frac{e^{a+bx}}{1+e^{a+bx}} \qquad (6)$$

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

$$MAPE = 100 \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \qquad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (8)$$

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%.

4. 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)

4.1. Forecast for consumer C1 is highlighted by hourly load curve presented in Fig. 9 and specific elements of characterization, given in Table 5.

Fig. 9 One week ahead hourly forecast for C1

Table 5. One week ahead forecast accuracy for C1

	MAPE	RMSE
24.11.2008-Monday	7.503933232	8.042164
25.11.2008-Tuesday	8.434014921	9.986919
26.11.2008-Wednesday	5.294470956	6.509274
27.11.2008-Thursday	8.515690096	9.874305
28.11.2008-Friday	5.953928064	7.535833
29.11.2008-Saturday	4.793994534	5.525859
30.11.2008-Sunday	6.379335167	6.985652
	MAPE	**RMSE**
	6.696480996	**7.780001**

Epochs=7   Weighting delta =0,0001

4.2.1. Forecast for consumer C2-1 is highlighted by hourly load curve presented in Fig. 10 and specific elements of characterization, given in Table 6.
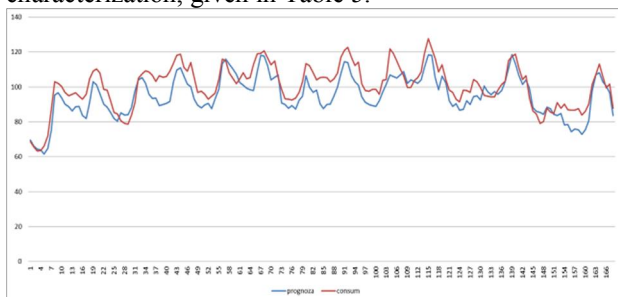

Fig. 10. One week ahead hourly forecast for C2-1

Table 6 One week ahead forecast accuracy for C2-1

	MAPE	RMSE
24.11.2008-Monday	28.75748331	0.137990808
25.11.2008-Tuesday	15.83795041	0.083503932
26.11.2008-Wednesday	12.95388861	0.080982726
27.11.2008-Thursday	13.58013874	0.06785188
28.11.2008-Friday	16.21944387	0.085042349
29.11.2008-Saturday	26.69097218	0.121860754
30.11.2008-Sunday	26.26036989	0.132411864
	MAPE	**RMSE**
	20.04289243	**0.101377759**

Epochs=284   Weighting delta =0,0001

4.2.2. Forecast for consumer C2-2 is highlighted by hourly load curve presented in Fig. 11 and specific elements of characterization, given in Table 7..
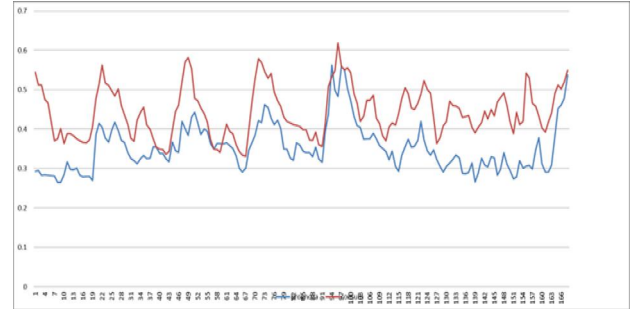

Fig. 11. One week ahead hourly forecast for C2-2

Table 7 One week ahead forecast accuracy for C2-2

	MAPE	RMSE
24.11.2008-Monday	10.59919333	0.298812838
25.11.2008-Tuesday	6.150937598	0.177721682
26.11.2008-Wednesday	4.513790748	0.140221502
27.11.2008-Thursday	4.240236127	0.141537919
28.11.2008-Friday	6.546728799	0.202048269
29.11.2008-Saturday	9.431161759	0.338922658
30.11.2008-Sunday	1.824768892	0.063414566
	MAPE	**RMSE**
	6.186688179	**0.194668491**

Epochs=30   Weighting delta =0,0001

4.3. Forecast for consumer C3 is highlighted by hourly load curve presented in Fig. 12 and specific elements of characterization, given in Table 8..
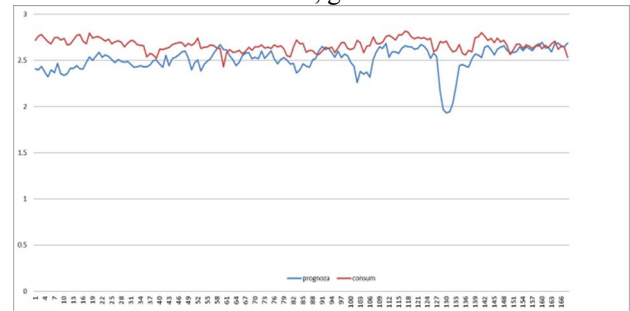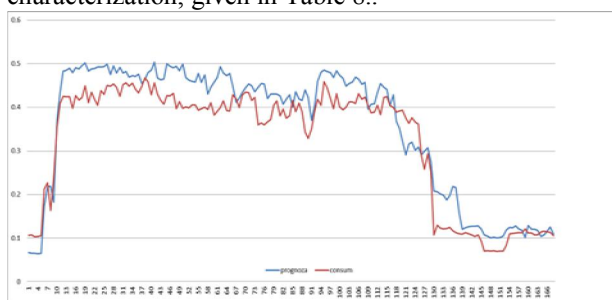

Fig. 12. One week ahead hourly forecast for C3

Table 8. One week ahead forecast accuracy for C3

	MAPE	RMSE
24.11.2008-Monday	20.27999671	0.056190517
25.11.2008-Tuesday	9.833870146	0.047871208
26.11.2008-Wednesday	13.5136903	0.06108795
27.11.2008-Thursday	12.04850749	0.053662749
28.11.2008-Friday	10.04786445	0.045929771
29.11.2008-Saturday	34.22835576	0.059480378
30.11.2008-Sunday	22.60971056	0.022042545
	MAPE	**RMSE**
	17.50885649	**0.049466445**

Epochs=35   Weighting delta =0,0001

5. CONCLUSION

Forecast consumption is the main element of analysis of this research, forecasting being the factors influencing the development or modification of decisions at various stages of management of the electricity supply service.

As shown in the graphics load curve obtained by superimposing the real and the forecast consumption curve, the software ability to detect and use temporary trends (daily, weekly, etc. ..) and seasonal trends or the entire series time consumption is relatively good in terms of ANRE requirements for electricity consumption self-forecast by consumers (MAPE <25%). In terms of forecasting consumption standards (MAPE <5%), the recommended ANRE MAPE are high.

Analysing the investigated consumer's behaviour we can conclude for each user, the following:

- C1 – although the database is relatively acceptable as a number of measurements (8760 hourly average power, over a year) ANN has easily processed the learning, 7 epochs, MAPE has an acceptable value of 6,69%. Errors are homogeneously distributed throughout the week, showing larger errors for weekdays and significantly lower errors for the other days;

- C2 – C2-1 having a database with a very small number of hourly measurements of average power 3781 ANN has processed the learning in 284 epochs, MAPE has an unacceptable value of 20,04%, mainly due to two factors: the very little number of data available for ANN learning, and transitional consumption, with a decrease inexistent in the ANN learning hypothesis; and the working transition from sugar production to the absence of production (conservation)

   – C2-2 database with a very small number of hourly measurements of average power 1001, ANN

has processed the learning quickly, in 30 epochs, MAPE has an acceptable 6.18%, taking into account two factors: the very limited data available for ANN learning and the use of transitional arrangements for the production from sugar beet production to the production from raw sugar

- C3 – although the database has an acceptable number of hourly measurements of average power 8760, ANN has processed the learning quickly, 35 epochs, MAPE has a large value 17,51%. Errors are not distributed homogeneously throughout the week, with a high percentage of errors for the weekend days. The cause of this high value of MAPE are the three changes in the consumption profile due to the two holiday periods of two weeks and the change of the working regime for two weeks from 3 shifts, at two shifts.

The results are below expectations and the software needs improvement. We will then attempt the implementation in the R-Statistics package of new techniques for forecasting, to compare and label the best type of forecast for a particular type of load curve (profile). We will try to achieve improvements to the package by adding features like using data that is not numerical, using weather forecasts modules using beside temperature, specific wind directions, special weather phenomena, etc.

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