SHORT TERM LOAD FORECASTING FOR A DISTRIBUTION OPERATOR IN ROMANIA

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Abstract - Forecasting the power demand and electricity consumption has a significant impact on the efficiency of electrical grid operation; the latter involves numerous decisions potentially generating significant costs such as power reserve planning, fuel supply planning, monitoring system security or planning energy transactions. The short-term load forecasting is expected to increase in the future due to the dramatic changes that occur in the energy sector, changes arising from the restructuring of this sector and the emergence of competition. This paper will present a Day Ahead Load Forecasting using artificial neural networks for a Distribution Operator in Romania. The results will be compared for two particular cases: one where it will be taken into account only the history of consumption and the other one is a naïve forecast.

Keywords: load forecasting, history of consumption, load profile, temperature, neural networks, naïve forecast

1. INTRODUCTION

The main objective of short term load forecasting is to predict the hourly loads, one day or even one week beforehand, which is necessary for the operational planning of the power system. Forecasting the power demand and electricity consumption has a significant impact on the efficiency of electrical grid operation; the latter involves numerous decisions potentially generating significant costs such as power reserve planning, fuel supply planning, monitoring system security or planning energy transactions. The short-term load forecasting is expected to increase in the future due to the dramatic changes that occur in the energy sector, changes arising from the restructuring of this sector and the emergence of competition. The full opening of the electricity market in Romania has determined the suppliers and the consumers new opportunities to maximize their profits by purchasing or selling energy on the liberated electricity market [1].

Strategies involving trading on the existent markets must take into consideration the load forecast of the consumption profile obtained by the consumers and suppliers. Due to this fact load forecasting is very important in reducing the costs. A distribution operator can be assimilated as a consumer due to the energy losses that occur during the consumption process.

This paper will present a day-ahead load forecasting for a distribution operator in Romania using artificial neural networks. The results will be compared with a naïve forecast that uses the electricity consumption of the past day type [2].

2. ARTIFICIAL NEURAL NETWORK APPROACH

The model uses a feed forward with back propagation neural network with two hidden layers. For simplicity it will be presented the algorithm for one hidden layer neural network. The model used can be generalized for a two hidden layer neural network [3].

The feed forward algorithm proposes multiplying the output of each neuron with the weight of the connexion:

$$- \ Net_j = \sum_{i=1}^{M} (w_{ij}(t) \cdot x_i), \quad j = 1..K..N \qquad (1)$$

$$- \ Net_k = \sum_{j=1}^{N} (w_{jk}(t) \cdot O_j) \quad k = 1..K..P \qquad (2)$$

where M, N, P – are the number of neurons from each layer. x_i, O_j are the input and output for the hidden layer. For the output values, the sigmoid function is used as activation function.

$$- O_j = f_{act}(Net_j) = \frac{1}{1+e^{(-Net_j - \theta_j)}} \quad \text{j = 1..K..N} \quad (3)$$

$$- Y_k = f_{act}(Net_k) = \frac{1}{1+e^{(-Net_k - \theta_k)}} \quad \text{k = 1..K..P} \quad (4)$$

where Y_k is the output of the neural network, and θ_j, θ_k are the biases for the sigmoid function towards the last two layers.
For the training set, the errors have been calculated as follows:

$$- \delta_k = f_{act}^{`} \cdot Net_j \cdot (D_k - Y_k) \quad \text{k = 1..K..P} \quad (5)$$

$$- \delta_j = f_{act}^{`} \cdot Net_j \cdot \sum_{k=1}^{P} (\delta_k \cdot W_{jk}(t)) \quad \text{j = 1..K..N} \quad (6)$$

where the $f_{act}^{`}$ is the derivative of the activation function, and D_k is the desired value obtained from the training set.

For the back propagation algorithm with learning constant and momentum constant, the weight adjustments are made as indicated below:

$$- W_{jk}(t+1) = \eta \cdot \delta_k \cdot O_j + m \cdot \Delta W_{ij}(t) \quad (7)$$

$$- W_{ij}(t+1) = \eta \cdot \delta_j \cdot X_i + m \cdot \Delta W_{ij}(t) \quad (8)$$

where η is the learning constant and ***m*** is the momentum constant [4], [7], [5].

The model used has the next configuration: 31 neurons in the input layer, 20 neurons in the first hidden layer, 8 neurons in the second hidden layer and one output neuron. The inputs used for this neural network are the following: the type of day and the type of the hourly interval [4, 5, 6]. These are coded binary as inputs for the 31 input values that the neural network has. It has been tested a series of 10 models and the best results are obtained by the one mentioned before. This model uses a training parameter with a value of 0.24 and the momentum constant value is 0. The training set uses a window of 336 rows (last two weeks) updated after a 24 hours forecast. The training process stops when the smallest mean absolute percentage error will reach a minimum in 450 epochs. From these values the last 8 values from the training set are used to validate the results [3]. [7].

$$- EMP = \frac{1}{N_T} \cdot \sum_{m=1}^{N_T} \sum_{k=1}^{P} (D_k^m - Y_k^m)^2 \quad (9)$$

- N_T - the number of data values from the training set

3. RESULTS

The results obtained by using the artificial intelligence model were compared with the naïve forecast. Modeling artificial neural network is a demanding task that implies understanding the functioning of ANN, as interpreting the results. In any circumstances the artificial neural networks approach supplies better results than the naïve forecast.
In order to measure the performance of the forecast the next statistical indicators is defined:

$$\text{- Percent forecast error: } re_t = \left(\frac{y_t - \tilde{y}_t}{y_t} \right) \cdot 100 \quad (10)$$

$$- MAPE = \frac{1}{n} \cdot \sum_{t=1}^{n} |re_t| \quad (11)$$

where $e_t = \tilde{y}_t - y_t$; e_t - the forecast error; $\tilde{y}_t$ - forecasted value; y_t - real value [1], [8];

If the artificial neural networks use artificial intelligence by training the network with a set of data called training set, the naïve forecast uses the electricity consumption obtained in the last day type of the past week in order to forecast the actual electricity consumption.

Other papers [9, 10] confirm that the ANN model chosen presents a good performance. A mean absolute percentage error of 3.57% is much better than the 4.50 % obtained by the naïve forecast. It must be mentioned the fact that the holydays have not been taken into consideration in the construction of this model. The data that has been forecasted includes the data for the year 2005. One week of each month has been forecasted except December. This was not possible because in December there aren't two weeks without holidays that can be used for the training set, in order to forecast one whole week.

What is important to be mentioned is the fact that on a daily consumption the forecast imposed by the distribution operator must be below 5%.

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Table 1. Monthly MAPE for ANN and NAIVE

Luna	*HOURLY*		*DAILY*	
2005	***ANN***	***NAIVE***	***ANN***	***NAIVE***
Ianuarie	**3,50%**	**2,86%**	**3,13%**	**2,63%**
Februarie	**2,98%**	**4,48%**	**2,49%**	**4,65%**
Martie	**2,21%**	**2,47%**	**1,22%**	**1,86%**
Aprilie	**3,96%**	**5,92%**	**1,23%**	**1,64%**
Mai	**4,73%**	**4,66%**	**3,01%**	**3,06%**
Iunie	**3,15%**	**4,14%**	**1,47%**	**3,00%**
Iulie	**3,80%**	**4,85%**	**3,37%**	**3,93%**
August	**4,10%**	**6,35%**	**2,44%**	**3,65%**
Septembrie	**3,15%**	**4,24%**	**1,59%**	**3,26%**
Octombrie	**3,38%**	**4,92%**	**2,67%**	**4,37%**
Noiembrie	**4,34%**	**4,59%**	**2,64%**	**2,92%**
Decembrie	-	-	-	-
Total	**3,57%**	**4,50%**	**2,29%**	**3,18%**

The results obtained by the ANN forecast present a 2.29% mean absolute percentage error, which is better by almost 1% than the naïve forecast. On the electricity market the balance costs can be reduced with approximately 80 000 Euros per year if the load forecast is improved by 1% [12, 13].

Table 2. MAPE – hourly interval MAPE values

Hourly interval	ANN	NAIVE	Hourly interval	ANN	NAIVE
Int.1	3,25%	3,71%	Int.13	3,80%	4,84%
Int.2	3,14%	4,04%	Int.14	3,51%	4,17%
Int.3	3,34%	4,36%	Int.15	3,12%	3,81%
Int.4	3,19%	4,00%	Int.16	3,46%	4,49%
Int.5	3,63%	4,89%	Int.17	3,81%	4,98%
Int.6	3,61%	4,85%	Int.18	3,56%	4,46%
Int.7	3,78%	4,17%	Int.19	4,01%	5,00%
Int.8	3,36%	4,24%	Int.20	3,97%	4,99%
Int.9	3,14%	4,40%	Int.21	3,16%	4,43%
Int.10	3,58%	5,04%	Int.22	3,38%	4,52%
Int.11	4,20%	5,09%	Int.23	3,94%	3,98%
Int.12	4,37%	5,70%	Int.24	3,67%	4,47%

At hourly interval level it can be easily observed that the mean absolute percentage error is lower for artificial intelligence model than in the case of the naïve forecast. However, the errors seem to be high in peak load demand as in off-peak load demand. The model must be improved by introducing other factors as temperature and humidity, which takes into consideration the human behavior and the warm-cold perception.

The most important evaluation for the forecast performance is done by calculating the errors at hourly level. It is known that prices on the day-ahead market, as on the balance market are higher during the week-days than on the week-ends.

Table 3. Monthly MAPE for ANN and NAÏVE – Week-days

2005	***WEEK-DAYS***	
Hourly	***ANN***	***NAÏVE***
17.01. - 21.01	**3,85%**	**3,27%**
14.01. - 19.02	**3,72%**	**5,49%**
20.01. - 24.03	**2,22%**	**2,59%**
18.04. - 22.04	**4,21%**	**5,54%**
23.05. - 27.05	**4,26%**	**4,57%**
06.06. - 10.06	**2,93%**	**3,78%**
25.07. - 29.07	**4,02%**	**5,55%**
15.08. - 19.08	**4,47%**	**6,29%**
05.09. - 09.09	**3,04%**	**5,02%**
10.10. - 14.10	**2,94%**	**3,77%**
21.11. - 25.11	**4,05%**	**4,66%**
-	-	-
Total	**3,61%**	**4,59%**

For a better evaluation of the cost reduction, table 3 and 4 offer the possibility to evaluate the statistical measures according to each month for week-days and week-ends separately.

Table 4. Monthly MAPE for ANN and NAÏVE – Week-ends

2005	***WEEK-ENDS***	
Hourly	***ANN***	***NAÏVE***
22.01. - 23.01	**2,63%**	**1,83%**
20.01. - 21.02	**1,73%**	**3,48%**
18.01. - 19.03	**2,30%**	**2,57%**
23.04. - 24.04	**3,34%**	**6,88%**
28.05. - 29.05	**5,91%**	**4,90%**
11.06. - 12.06	**3,69%**	**5,06%**
30.07. - 31.07	**3,25%**	**3,12%**
20.08. - 21.08	**3,16%**	**6,50%**
10.09. - 11.09	**3,42%**	**2,28%**
15.10. - 16.10	**4,47%**	**7,81%**
26.11. - 27.11	**5,05%**	**4,41%**
-	-	-
Total	**3,54%**	**4,44%**

The errors during the week-days are higher than those in the week-ends. The predictability of the Monday – Friday days is poorer because of the load profile variations that can appear due to several factors: fast temperature variation, precipitations, and outages or the stop of an important consumer. The total MAPE for week-days is 3.61% for ANN model against 4.59% for the naïve model, in case of considering only the forecast errors obtained for the working days. During the week-ends the forecast errors are lower cumulating 3.54% for the ANN model and 4.44% for the naïve model.

Table 5. MAPE for the entire analyzed period for each day type - hourly

Hourly	*2005*	
DAY TYPE	*ANN*	*NAÏVE*
Luni	**4,01%**	**4,97%**
Marți	**3,84%**	**4,60%**
Miercuri	**3,26%**	**4,69%**
Joi	**3,55%**	**4,12%**
Vineri	**3,40%**	**4,59%**
Sâmbătă	**3,01%**	**4,13%**
Duminică	**4,07%**	**4,75%**

From the results presented in table 5 it is obvious that at day type level the best forecast is achieved for Saturday. For both methods the load forecast obtained Sunday and Monday indicate the fact that these two day type present great volatility and are harder to forecast than the other days.
Along with the presentation of the mean absolute percentage errors the distribution of the absolute percentage errors can be visualized for a better perception of the accuracy obtained by the forecast (fig. 1, 2, 3, 4). At hourly level the forecast must be improved. Almost 65% of the forecasted data present errors lower than 4%. The results obtained by using a Naïve model are poorer, with a 55% error distribution under 4% absolute percentage deviation.

For the daily consumption the forecast is lower because the hourly load can be compensated during the entire 24 hour load profile. 85% of the errors are lower than 4% in the case of the artificial neural network in comparison with the naïve model which has 70% accuracy for the same imposed error level. The superiority of the artificial intelligence model is obvious, a better error distribution and lower errors can be obtained after utilizing neural networks. As it has been mentioned previously the limits imposed by the distribution operator are to have errors below 5% for the daily consumption. In 93.5% of the cases this condition is accomplished by the neural network model. In comparison, the naïve forecast accomplishes this condition in lower than 80% of the forecasted days.

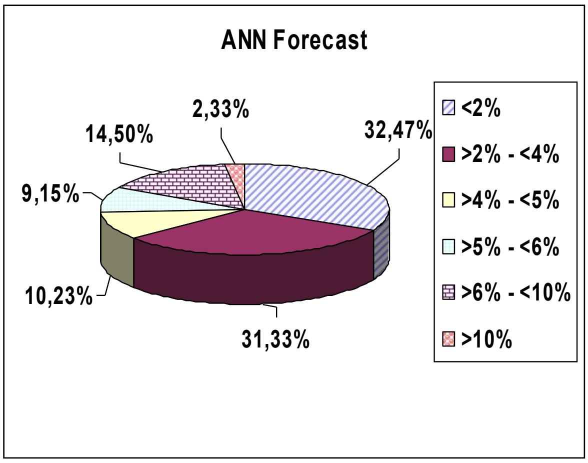

Fig. 1. Absolute percentage errors distribution - Hourly

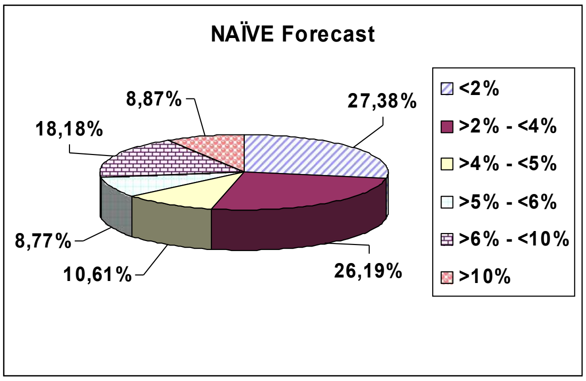

Fig. 2. Absolute percentage errors distribution - Hourly

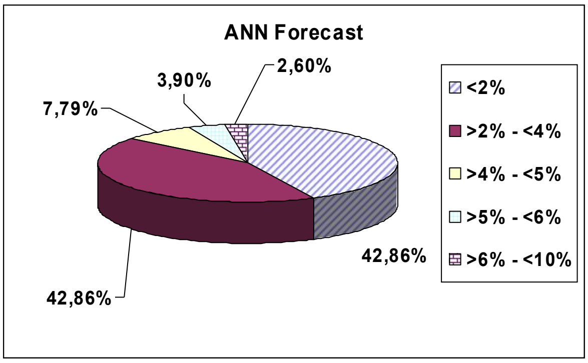

Fig. 3. Absolute percentage errors distribution -Daily

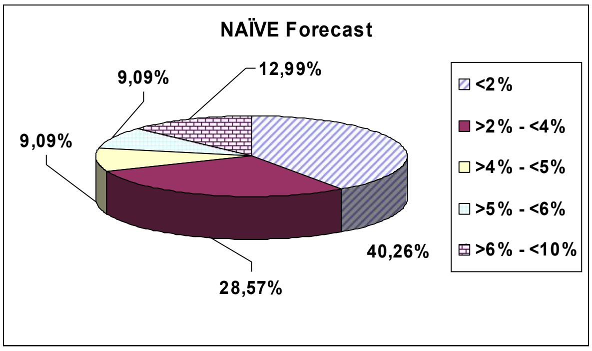

Fig. 4. Absolute percentage errors distribution - Daily

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4. CONCLUSIONS

In the context of an acute economic crisis, assessing opportunities to reduce the invoice cost of electricity could lead to significant results and rapid depreciation of investments made. Although the consumer can chose to purchase energy from the regulated market, as from the liberated market, at high values of consumption, daily load forecasting is implied [1], [8].

The opening of the electricity market in Romania has offered the market participants, especially the consumers the possibility to reduce their bill costs. This fact is possible only if the market participants pay close attention to their actual load profile. The existence of a day-ahead market in Romania makes it possible to adjust the load profile and reduce the risk to trade energy from the balance market, where the prices are high for the energy purchase and low for electricity selling.

A distribution operator can be seen as a consumer due to the fact that the energy losses that appear during electricity consumption can represent over 10% of the actual load. Improving load forecasting could offer a good possibility to reduce commercial charges. For the analyzed distribution operator from Romania, forecast improvement with 1% could lead to 80 000 Euros cost reduction per year.

The results obtained by the artificial neural network model [2, 5, 11] are superior to those obtained by the naïve forecast model. From the information supplied by the distribution operator the daily consumption error must be lower than 5%. The artificial intelligence model has a mean absolute percentage error of 2.29% for the analyzed period, with over 93% of the errors below the 5% imposed limit.

The neural network model will be developed in order to include other factors that can be crucial to the load profile description. Other parameters that can be taken into consideration as neural network inputs can be temperature, cloud cover or humidity.

Although the results present a good performance compared with others published papers from the technical literature [9, 10], the model must be extended in order to increase the forecast accuracy.

It can be mentioned the fact that there other methods that applied obtain good results [14, 15, 16], time series models or causal. In order to improve the forecast performance it might be useful to combine to or maybe three such methods.

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