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Enhanced ANN Approach for Load Curve Forecast

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Abstract—**The load curve forecasting problem is discussed within the current paper. The daily load curves are forecasted. The problem is tackled using artificial neural networks (ANN). Authors are proposing an enhanced algorithm that includes nonlinear optimization techniques, such as conjugate gradient. A software-tool has been developed for this purpose. Case study refers to a real distribution network operator from the Western part of Romania. The results are compared with the ones obtained without implementing any optimization techniques. Algorithm convergence and forecast quality are improved in case of ANN based algorithm enhanced with conjugated gradient method.**

Keywords-daily load curve; forecast; ANN; backpropagation; nonlinear optimization techniques; conjugate gradient.

I. INTRODUCTION

Load forecasting represents the activity based on consumed power evolution prediction using computing and known data analysis, having as a goal to finally obtain a concordance between the estimated power demand and the one that has been consumed in reality.

Medium-term and long-term load forecasting methods are performed considering 5-10 years, respectively 10-25 years.

The econometric approach combines economic data with statistical techniques for load forecasting [1]. The relation between the power consumption (dependent variable) and factors that are influencing the consumption (independent variables) is estimated. It is based on least square method [2] or time series method [3]. In [4] an econometric model based on regression method including wavelet network is presented. Parameter model identification is performed based on solving an optimization nonlinear quadratic problem [2]. The temperature influence over the consumed power is also taken into consideration, in a probabilistic manner.

The "end-use" [1] approach directly estimates the energy consumption using a large domain of available information related to final consumed power and to final user. Statistical consumed power data and dynamic change represent the background for the load forecast. The model applies to residential consumers, commercial ones and, also, industrial ones. According to them, the power demand is modelled as a function of market requests.

There are also presented within the literature several approaches dealing with artificial intelligence methods (ANN – artificial neural networks, evolutive computing, fuzzy based approaches, etc.).

PSO (Particle Swarm Optimization) based algorithm is used in [5]. The goal is to minimize the error associated to the estimated model parameters. The case studies are referring to the load forecasting in case of two real distribution networks and to the peak power. Results are compared with the ones obtained for least square method, conclusions being favorable to the new one.

In [6] the long-term load forecasting is performed based on time series approached in fuzzy manner. Known data (for the Jiangsu area in China) are corresponding to 12 years period: the 1st 10 years are used for load forecasting performing for years 11 and 12, errors comparing with the real values being 2-4 %. The fuzzy logic technique is also used in [8], but the case study is focused on a power distribution company in Turkey.

The short-term load forecasting is performed for 1-5 years period. The ANNs have been used for load forecasting starting with [8]. Usually, backpropagation architecture ANNs are used. They are using real variables functions and supervised learning.

In [9] a mixed approach is proposed, between ANNs and ARIMA (autoregressive integrated moving average with exogenous variables) time series. The linear known load data component is approached using ARIMA and the non-linear one, with ANNs. The qualities of such an approach are highlighted based on analyzed case studies with empirical data.

In [10] two models are used for short-term load forecasting: backpropagation ANN and hybrid model (ANN-fuzzy approach). The case study refers to the New England (USA) consumption area, highlighting the superiority of the 2nd model.

The application presented in [11] refers to the power consumption from a high voltage / medium voltage substation in Iran, the one presented in [12] refers to a power consumption area in Ontario, Canada. In [13] power consumption forecasting is performed for the case of the Egyptian Unified System. All these cases are based on ANNs forecasting methods.

In [14] the ANN based load forecasting is performed for the case when the correlation degree for the known data is extremely reduced.

A mixed technique for load forecasting is used in [15] combining an inference adaptive neuro-fuzzy system (ANFIS), based on Takagi-Sugeno model.

In the current paper, the *enhancement* of the algorithm refers to the use of conjugate gradient method (Fletcher-Reeves) [2] to improve its convergence and forecast quality. Finally, a comparison is performed between the results obtained in case of the algorithm with conjugate gradient method implemented and the case without.

Following the introduction already presented, the 2nd section is focusing on presenting the ANN based forecasting mechanism. The results provided by the developed algorithm are discussed within the 3rd section. Case study refers to a real distribution network operator from the Western part of Romania. The 4th section synthesizes the conclusions.

II. ANN Based Load Curve Forecasting

Load forecast is performed using an ANN type multi-layer perceptron, with backpropagation algorithm.

Daily load curves are considered to be known (as input data) for a specific day of the year, for a period of *n* years. The forecast is requested to be performed for the following years, meaning *n+1*, *n+2, ...*

The algorithm is briefly described in the following:

1. input data are introduced: ANN number of inputs and outputs, known load curves, number of neurons from the hidden layer, learning rate, range where the random values are going to be generated, maximum admitted error, maximum number of computing steps;
2. weights for the neurons of the hidden and output layers are randomly initialized;
3. activation step for the hidden and output layers is randomly initialized;
4. the 1st learning epoch is initialized;
5. known load curves' index is initialized with the 1st one;
6. *forward* cycle is performed:
   6.1. output values for the hidden layer neurons are computed;
   6.2. output values for the output layer neurons are computed;
   6.3. epoch square error is computed for each output;
7. *backward* cycle is performed for the current value of the epoch:
   7.1. errors gradients' value are computed for the output layer neurons;
   7.2. errors gradients'value are computed for the hidden layer neurons;
8. *adjusting* stage is performed for the current value of the epoch:
   8.1. weights gradients' values are computed for the hidden layer neurons;
   8.2. weights gradients' values are computed for the output layer neurons;
9. known load curves' index is checked. If the last known load curve is not reached, then the index is increased and the algorithm is continuing with point 6). If all the models have been used, point 10) is going to follow;
10. if the algorithm is blocked in a local minimum (based on the gradients' absolute values), the computing process is cancelled and the entire procedure is started once more with step 2). Contrary, algorithm is continued with step 11);
11. to increase the ANN performance the conjugate gradient is applied to compute the weights' searching directions and searching step:
    11.1. β value is computed to correct the searching direction based on the "previous" history:

$$\beta = \frac{\boldsymbol{g}^{k-1}\cdot(\boldsymbol{g}^{k-1})^t}{\boldsymbol{g}^{k-2}\cdot(\boldsymbol{g}^{k-2})^t} = \frac{(g_1^{k-1})^2+(g_2^{k-1})^2+\cdots+(g_n^{k-1})^2}{(g_1^{k-2})^2+(g_2^{k-2})^2+\cdots+(g_n^{k-2})^2} \quad (1)$$

where: k – computing step; $\boldsymbol{g}$ –gradients' vector;

    11.2. hidden and output layers neurons' searching directions ($\boldsymbol{d}$) are computed:

$$\boldsymbol{d}^{k-1} = -\boldsymbol{g}^{k-1} + \beta\cdot\boldsymbol{d}^{k-2} \quad (2)$$

    11.3. parabolic interpolation method is applied to find the minimum position along the searching direction [2]:

$$\alpha = \frac{h}{2}\cdot\frac{3\cdot f_0 - 4\cdot f_1 + f_2}{f_0 - 2\cdot f_1 + f_2} \quad (3)$$

where: h – interpolation step; f_0, f_1, f_2– objective function (index) value for the points within the interpolation process:

$$\begin{aligned} f_0 &= f(\boldsymbol{x}^{k-1}) \\ f_1 &= f(\boldsymbol{x}^{k-1} + h\cdot\boldsymbol{d}^{k-1}) \\ f_2 &= f(\boldsymbol{x}^{k-1} + 2\cdot h\cdot\boldsymbol{d}^{k-1}) \end{aligned} \quad (4)$$

    11.4. weights ($\boldsymbol{x}$) for the neurons' of the hidden and output layers are computed:

$$\boldsymbol{x}^{k} = \boldsymbol{x}^{k-1} + \alpha\cdot\boldsymbol{d}^{k-1} \quad (5)$$

12. hidden and output layer neurons' values, respectively the square epoch error are computed
13. based on the square errors' sum (total error) the stopping criteria are checked:
    - if total error is below the maximum admitted one, then the computing process finishes and also the learning process. Step 14 is following;
    - if total error is greater than the maximum admitted one, then the computing process is not finished. The maximum number of computing steps is checked:
      - if the maximum number of computing steps is over-passed, all the process is repeated from step 2), with new values for neurons' weights and activation steps;
      - contrary, the next computing step is performed and the algorithm runs with step 7);
14. the forecast for the following years is able to be performed based on the results using the last computed values for neurons' weights.

The software-tool has been developed in Matlab environment based on the presented algorithm. No toolbox from Matlab environment has been use.

Using the *ANN configuration* option, the user is able to set the ANN configuration, such as: number of neurons for the input and output layers, number of hidden layers and involved neurons, number of known load curves, the range used for the random initialized variables, learning rate, maximum admitted error, maximum computing steps.

III. Results and Discussions

Case study refers to a real distribution network operator from the Western part of Romania. The known daily load curves for the 2001-2010 period are presented in Table 1 and Fig. 1. Hourly loads are considered for each load curve. The selected day refers to the most significant summer day – June 21st. The forecast is performed for the next three years (2011, 2012, 2013).

The known daily load curves for 2011-2013 period are presented in Table 2 and Fig. 2. The same summer day has been considered as for the known curves. These data are used to validate the forecast.

TABLE 1. LOAD CURVES FOR 2001-2010 PERIOD [MW] – KNOWN DATA

Year / hour	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
1	185.6	182.6	179.5	174.2	168.8	167.3	165.7	160.4	159.5	158.6
2	182.6	180.4	178.2	172.7	167.1	168.7	170.3	151.1	153.9	156.8
3	180.5	179.7	178.9	172.4	165.9	171.0	176.1	163.5	171.3	179.0
4	182.9	180.7	178.5	168.6	158.7	160.5	162.4	167.1	170.1	173.2
5	186.6	183.3	180.0	171.8	163.5	171.4	179.3	174.2	168.5	162.7
6	191.2	188.6	185.9	176.3	166.6	171.0	175.5	170.5	157.8	145.1
7	186.8	185.2	183.7	175.8	167.9	166.6	165.2	163.9	156.1	148.3
8	203.2	205.8	208.5	196.3	184.2	179.7	175.3	169.1	162.2	155.3
9	212.1	228.3	244.4	222.2	200.0	188.7	177.3	200.9	195.5	190.1
10	211.8	227.2	242.7	223.2	203.7	197.8	191.8	221.7	203.9	186.1
11	204.6	218.6	232.5	218.3	204.1	194.2	184.3	211.7	207.4	203.0
12	201.5	203.1	204.7	201.3	197.9	183.1	168.2	186.1	185.5	184.9
13	192.7	200.7	208.7	199.1	189.4	176.0	162.6	180.2	175.2	170.1
14	188.6	203.1	217.6	202.7	187.8	182.6	177.4	198.5	180.8	163.1
15	183.9	196.8	209.6	198.8	188.1	175.9	163.6	182.0	178.0	174.0
16	172.4	182.2	192.1	182.9	173.8	175.2	176.7	189.8	174.0	158.2
17	177.1	186.3	195.5	183.1	170.8	171.0	171.2	189.3	177.5	165.8
18	175.0	187.0	199.0	184.4	169.7	174.6	179.5	192.0	176.8	161.6
19	171.3	185.6	199.9	180.7	161.5	164.5	167.6	204.3	184.6	164.8
20	170.4	168.1	165.9	160.1	154.3	153.5	152.8	184.3	173.4	162.6
21	192.4	188.4	184.4	174.6	164.8	151.5	138.3	159.5	166.2	172.9
22	199.9	193.8	187.7	186.8	185.8	166.5	147.3	156.8	169.0	181.1
23	226.3	225.2	224.1	218.3	212.5	201.9	191.3	193.1	192.1	191.1
24	229.6	220.0	210.5	206.4	202.2	194.1	186.0	188.9	184.0	179.1

TABLE 2. LOAD CURVES FOR 2011-2013 PERIOD [MW] – FORECAST VALIDATION

Year / hour	2011	2012	2013
1	152.0	144.5	142.8
2	150.5	145.6	136.4
3	160.4	161.7	150.0
4	154.1	149.0	143.9
5	154.1	146.1	148.3
6	148.5	142.9	140.2
7	147.2	148.6	136.7
8	154.1	145.0	140.2
9	174.7	168.9	163.0
10	183.7	179.5	175.2
11	194.7	196.3	184.3
12	168.7	167.1	160.6
13	162.0	155.7	158.8
14	166.3	158.4	158.5
15	164.3	164.7	156.8
16	163.5	160.0	156.5
17	166.0	169.0	160.1
18	166.4	159.6	160.8
19	168.1	159.0	161.0
20	162.9	159.4	159.0
21	150.1	150.0	141.0
22	152.7	143.7	143.3
23	176.9	177.0	168.2
24	170.5	164.6	164.8

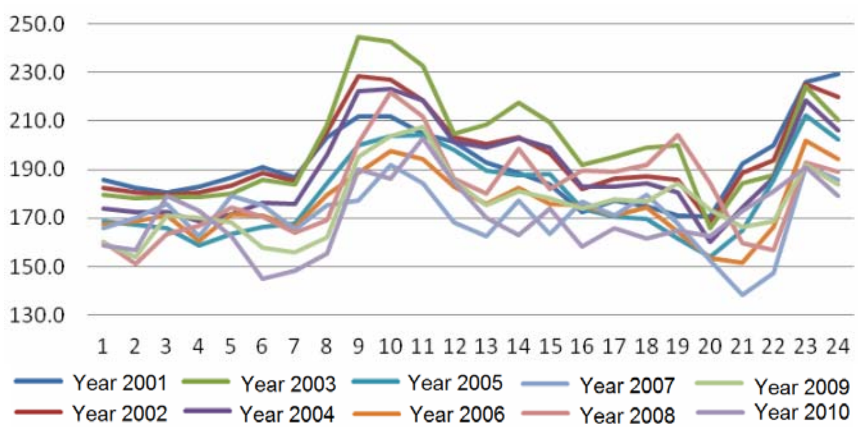

Fig. 1. Load curves' variation for 2001-2010 period [MW]

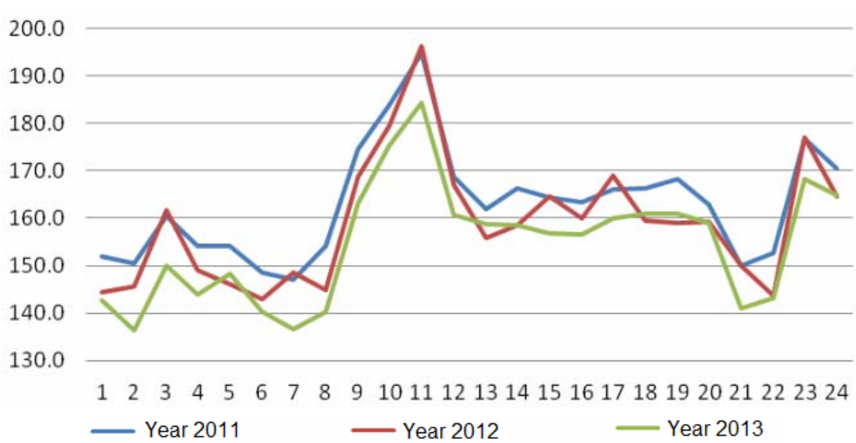

Fig. 2. Load curves' variation for 2011-2013 period [MW]

A brief analysis of the provided data highlights from the beginning the following conclusions:

- for the 2001-2010 period there is a power decrease tendency for the entire time horizon;
- load curves are crossing between them, thus their shape is different (they are not fully correlated);
- for the 2011-2013 case the power decrease tendency is maintaining;
- load curves correlation degree is relatively reduced (from the time evolution and daily shape point of view).

The load curve forecasting has been performed using the software-tool without conjugate gradient and with conjugate gradient. The results are presented in Tables 3-5 and Figs. 6-8.

TABLE 3. COMPARATIVE FORECAST RESULTS FOR 2011 [MW]

Hour	Known value	Without conjugate gradient			With conjugate gradient		
		Fore-casted value	Forecast error [%]	Standard deviation	Fore-casted value	Forecast error [%]	Standard deviation
1	152.0	153.3	0.9	0.8	149.9	-1.4	1.9
2	150.5	152.4	1.2	1.5	145.3	-3.5	12.0
3	160.4	163.6	2.0	4.0	162.1	1.0	1.1
4	154.1	159.4	3.4	11.9	155.0	0.6	0.3
5	154.1	154.1	0.0	0.0	160.3	4.0	16.0
6	148.5	151.1	1.8	3.1	148.3	-0.2	0.0
7	147.2	152.0	3.2	10.6	148.1	0.6	0.3
8	154.1	154.0	-0.1	0.0	150.2	-2.5	6.3
9	174.7	163.2	-6.6	43.3	178.2	2.0	4.1
10	183.7	162.5	-11.5	133.1	187.4	2.0	4.0
11	194.7	170.5	-12.4	154.2	195.4	0.4	0.1
12	168.7	164.3	-2.6	6.7	172.1	2.1	4.2
13	162.0	161.4	-0.4	0.1	162.0	0.0	0.0
14	166.3	161.2	-3.1	9.3	167.7	0.9	0.8
15	164.3	164.7	0.2	0.0	166.0	1.1	1.1
16	163.5	161.7	-1.1	1.2	165.1	1.0	0.9
17	166.0	164.7	-0.8	0.6	168.4	1.4	2.1
18	166.4	165.7	-0.4	0.2	166.8	0.3	0.1
19	168.1	168.0	-0.1	0.0	168.1	0.0	0.0
20	162.9	163.7	0.5	0.2	161.0	-1.2	1.5
21	150.1	170.1	13.3	177.6	148.7	-0.9	0.9
22	152.7	173.3	13.5	182.8	151.9	-0.5	0.2
23	176.9	182.8	3.3	11.1	177.7	0.5	0.2
24	170.5	182.2	6.9	47.1	169.7	-0.5	0.2
		Total		799.4	Total		58.5

TABLE 4. COMPARATIVE FORECAST RESULTS FOR 2012 [MW]

Hour	Known value	Without conjugate gradient			With conjugate gradient		
		Fore-casted value	Forecast error [%]	Standard deviation	Fore-casted value	Forecast error [%]	Standard deviation
1	144.5	151.7	5.0	25.1	144.9	0.3	0.1
2	145.6	151.3	3.9	15.1	140.3	-3.7	13.3
3	161.7	152.2	-5.9	34.5	158.5	-2.0	4.0
4	149.0	151.0	1.3	1.8	150.8	1.2	1.4
5	146.1	151.8	3.9	15.0	157.5	7.8	61.2
6	142.9	152.3	6.5	42.6	143.6	0.5	0.2
7	148.6	152.1	2.4	5.6	144.2	-3.0	8.9
8	145.0	157.6	8.7	75.8	144.0	-0.7	0.5
9	168.9	177.9	5.3	28.5	172.0	1.9	3.5
10	179.5	189.3	5.4	29.6	183.0	1.9	3.8
11	196.3	196.4	0.1	0.0	192.5	-1.9	3.8
12	167.1	164.5	-1.6	2.4	167.3	0.1	0.0
13	155.7	161.6	3.7	14.0	158.0	1.5	2.1
14	158.4	164.9	4.1	16.6	162.5	2.5	6.5
15	164.7	163.0	-1.0	1.0	161.5	-1.9	3.6
16	160.0	158.0	-1.2	1.5	161.6	1.0	1.0
17	169.0	159.0	-5.9	34.8	165.7	-1.9	3.6
18	159.6	159.9	0.2	0.0	163.4	2.3	5.5
19	159.0	159.9	0.6	0.3	163.9	3.1	9.5
20	159.4	157.9	-0.9	0.9	159.2	-0.1	0.0
21	150.0	156.2	4.1	17.0	143.4	-4.4	19.5
22	143.7	159.1	10.7	115.1	147.0	2.3	5.5
23	177.0	186.8	5.5	30.8	172.0	-2.8	7.8
24	164.6	177.4	7.7	59.9	164.8	0.1	0.0
		Total		568.1	Total		165.4

TABLE 5. COMPARATIVE FORECAST RESULTS FOR 2013 [MW]

Hour	Known value	Without conjugate gradient			With conjugate gradient		
		Fore-casted value	Forecast error [%]	Standard deviation	Fore-casted value	Forecast error [%]	Standard deviation
1	142.8	150.8	5.6	31.7	139.8	-2.1	4.3
2	136.4	151.3	10.9	119.5	135.3	-0.8	0.7
3	150.0	166.6	11.1	122.6	154.6	3.1	9.4
4	143.9	153.8	6.9	47.1	146.4	1.7	2.9
5	148.3	150.5	1.4	2.1	154.7	4.3	18.7
6	140.2	148.1	5.6	31.7	139.0	-0.9	0.7
7	136.7	149.7	9.5	90.3	140.4	2.7	7.4
8	140.2	147.1	5.0	24.6	137.8	-1.7	3.0
9	163.0	169.9	4.2	17.7	165.7	1.6	2.7
10	175.2	180.8	3.2	10.0	178.6	1.9	3.6
11	184.3	196.6	6.7	44.8	189.6	2.9	8.4
12	160.6	165.1	2.8	7.8	162.3	1.1	1.1
13	158.8	151.8	-4.4	19.6	154.0	-3.0	8.9
14	158.5	152.9	-3.5	12.6	157.1	-0.9	0.8
15	156.8	157.8	0.7	0.4	156.8	0.1	0.0
16	156.5	151.1	-3.5	12.0	158.0	0.9	0.9
17	160.1	157.7	-1.5	2.2	163.0	1.8	3.3
18	160.8	149.8	-6.8	46.7	159.7	-0.7	0.5
19	161.0	149.7	-7.0	48.5	159.4	-1.0	0.9
20	159.0	150.8	-5.1	26.5	157.2	-1.1	1.3
21	141.0	145.7	3.4	11.2	138.0	-2.1	4.5
22	143.3	144.5	0.8	0.7	142.1	-0.8	0.6
23	168.2	174.4	3.6	13.3	166.4	-1.1	1.2
24	164.8	160.3	-2.7	7.3	160.0	-2.9	8.3
		Total		750.8	Total		94.2

Table 6 presents the synthesis of the global performances indices in case of the ANN based forecasting with and without conjugate gradient method.

TABLE 4. GLOBAL PERFORMANCE INDICES COMPARATIVE ANALYSIS

	ANN without conjugate gradient	ANN with conjugate gradient
s_{2011}	799.4	58.5
s_{2012}	568.1	165.4
s_{2013}	750.8	94.2
s_{total}	2118.3	318.1

Comparative analysis of the results points-out the following remarks:

- ANN with conjugate gradient based results are, without any doubt, superior to the ones without conjugate gradient – global quality index is 318.1 compared with 2118.3 (meaning one magnitude order);

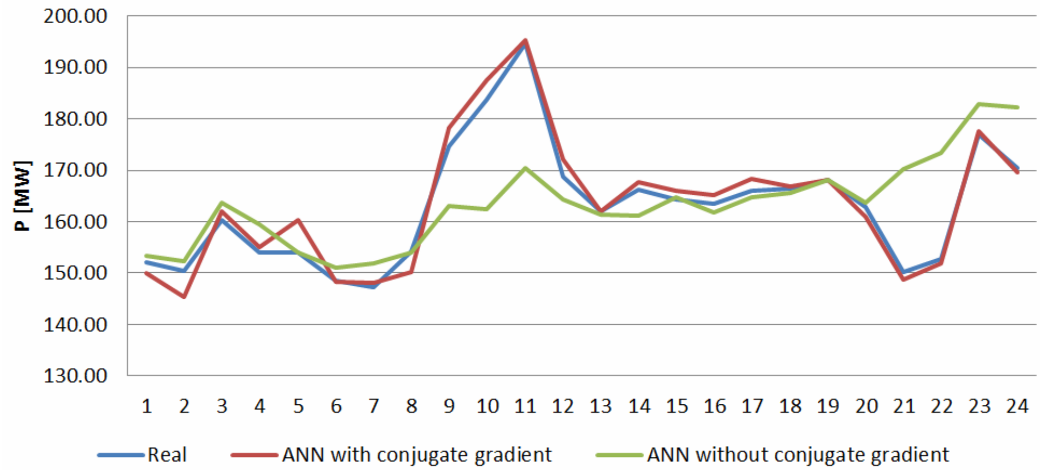

Fig. 6. Comparative forecast results for 2011

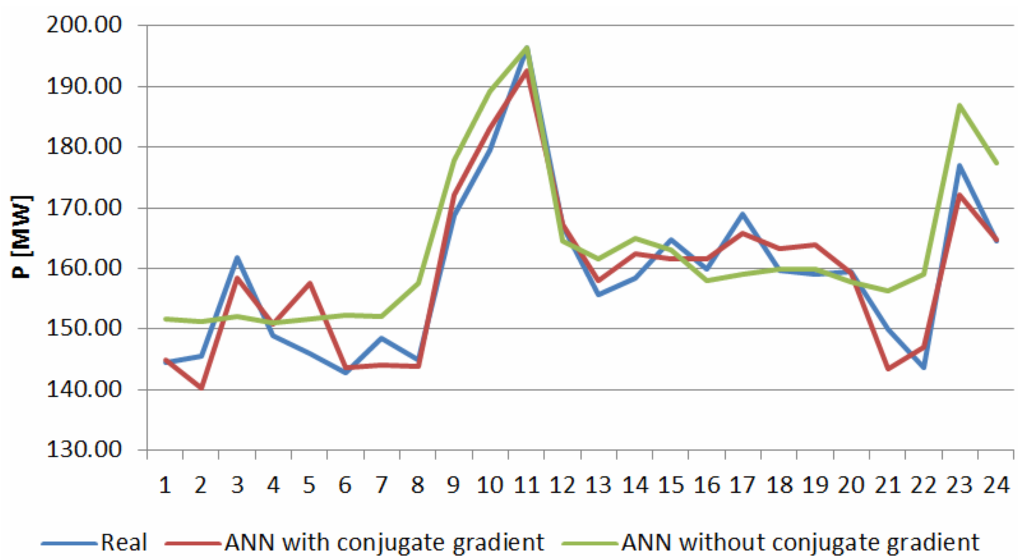

Fig. 7. Comparative forecast results for 2012

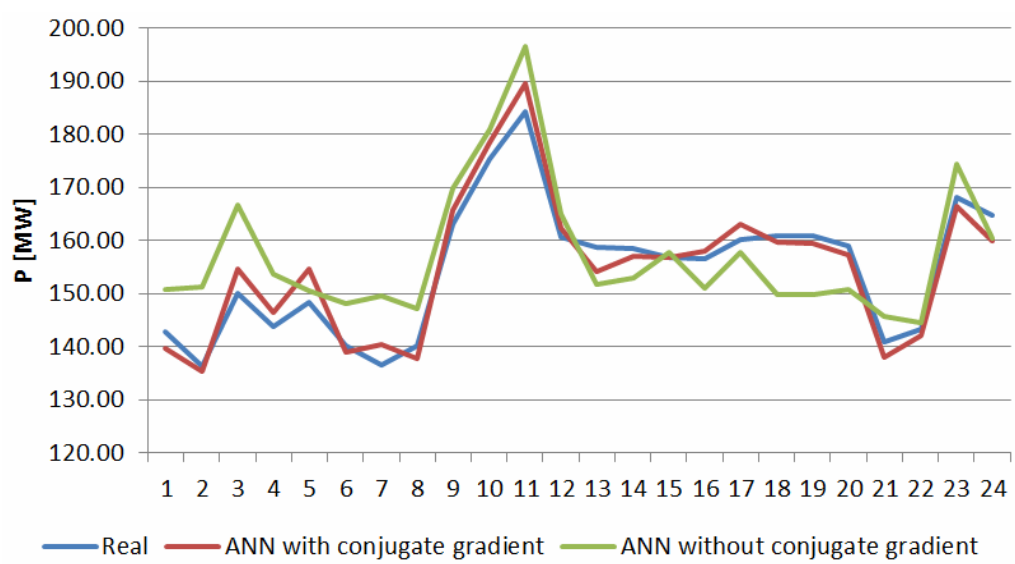

Fig. 8. Comparative forecast results for 2013

- same conclusion is valuable for the yearly quality indices' values – 58.5 compared with 799.4 (2011), 165.4 compared with 568.1 (2012), 94.2 compared with 750.8 (2013);
- maximum error of the forecasted values compared to the real ones is much lower in case of the enhanced algorithm (7.8 % compared with 13.5 %);
- same conclusion is sustained for the forecast yearly maximum errors – 4.0 % compared with 13.5 % (2011), 7.8 % compared with 10.7 % (2012), 4.3 compared with 11.1 % (2013);
- an improvement from 4.2 % to 1.6 % has been recorded in case of the absolute mean error, for the 3 considered years;
- absolute mean error for the three years has the following evolution: 1.2 % compared with 3.7 % (2011), 2.0 % compared with 4.0 % (2012), 1.7 % compared with 4.8 % (2013);
- figs. 6-8 are proving that the enhanced algorithm (red colour curve) "catches" much better the real load curves' shape (green colour curve) for the 2011 - 2013 years.

IV. CONCLUSIONS

For all the analysed cases the forecast error for the enhanced algorithm is smaller than the one corresponding to the algorithm without conjugate gradient.

Based on the provided analysis it has been concluded to improve the ANN based load forecasting with nonlinear optimization techniques (conjugate gradient – Fletcher-Reeves algorithm).

Considering the actual performance of the computing technique such a request is fully rightfully. There are no constraints regarding the computing effort or time.

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